Commercial Fishing Patterns in Australia's Northern Prawn Fishery and Implications for Management.

by

Elkana Ngwenya

BSc [Hons], MSc [Economics] (UZimbabwe), GradCertEd (UTas)

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DECLARATION

I do hereby declare that this thesis contains no material which has been accepted for an award of any higher degree or graduate diploma in any tertiary institution and that to the best of my knowledge and belief, the thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

Elkana Ngwenya (21 October 2001)

ABSTRACT

This thesis is focussed on the variation in fishing patterns realised by commercial fishers in Australia's Northern Prawn Fishery (NPF). An analytical framework is developed for use as a tool to help fishery managers understand commercial fishers' decision making and the subsequent fleet dynamics in commercial fisheries and their implications for fishery management. The thesis provides a framework based on Markovian theory that permits a description of the spatial and temporal allocation of fishing effort, and allows for the simulation of fleet movement in response to fishery management policy changes. The relocation of fishing effort between fishing grounds, over time, defines the spatial and temporal dynamics of fleet movement. Data on fishing locations of individual vessels are used to obtain a spatial and temporal series of transition probabilities, which are then used for describing and forecasting commercial fishing behaviour. These transition probabilities represent the likelihood of effort allocation to selected fishing grounds, over any two consecutive time periods. The ordinary Markov model relies solely on the historical transitions for the entire fleet across particular fishing grounds during a selected fishing period. However, since the transitions made by fishers are the outcome of economic behaviour and decision making in fishing, the variation in transition probabilities and the fishing patterns realised by commercial fishers are explained in the thesis using the multinomial logit (MNL) approach. To capture fishers' response to fishery policy, the ordinary Markov model is enhanced using estimates from the MNL model. This enriched Markov model, referred to as the MNL Markov, requires data on policy variables and characteristics of fishers and fishing grounds. Although not primarily policy-oriented, the effects of shortening the fishing season and closing selected fishing grounds are illustrated by inspecting the marginal effects of policy variables from the MNL Markov and evaluating the limiting distribution of transition probabilities in the ordinary Markov model. The results obtained in the thesis suggest that there is scope for fishery managers to use such models to forecast changes in commercial fishing patterns in the NPF that result from management changes such as shortening the fishing season and closing selected fishing grounds.

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DEDICATION

To all the following family members, relatives and teachers I have lost.

Emmanuel Dengu (teacher)
Edward Mabusa (teacher)
Isaac Mutanga (brother-in-law)
Kupakwashe Mutanga (niece)
Thelani Ndlovu (grandmother)
Frank Ngwenya (brother)
Nosizwe Ngwenya (sister)
Kembo Ngwenya (brother)

Their special memory has kept me hopeful.

TABLE OF CONTENTS **PAGE**

LIST OF ABBREVIATIONS

AB	Albatross Bay
ABARE	Australian Bureau of Agricultural Resource Economics
BPS	Banana Prawn Season
DAYS	Calender Day of the Month
CPUE	Catch Per Unit Effort
CSIRO	Commonwealth Scientific and Industrial Research Organisation
DAY	Day of Fishing
DGPS	Differential Global Positioning Satellite
DW	Durbin Watson statistic
CYCLEDAY	Effects of Cycles of Days
ECM	Error Component Method
FS	Fishing Season
GIS	Geographic Information Systems
GPS	Global Positioning Satellite
GoC	Gulf of Carpentaria
JBG	Joseph Bonaparte Gulf
KPF	Kimberley Prawn Fishery
MZ	Management Zone
MSY	Maximum Sustainable Yield
MAD	Mean Absolute Deviation
MAPE	Mean Average Percentage Error
ME	Mean Error
MPE	Mean Percentage Error
MSE	Mean Square Error
MONTH	Month of Fishing
MNL	Multinomial Logit
NPF	Northern Prawn Fishery
NORPAC	Northern Prawn Fishery Advisory Committee
NPFAG	Northern Prawn Fishery Advisory Group
NORMAC	Northern Prawn Management Advisory Committee
OLS	Ordinary Least Squares
CATCH1	Prawn Catch in State 1
CATCH2	Prawn Catch in State 2
CATCH3	Prawn Catch in State 3
SUR	Seemingly Unrelated Regression
SFG	Statistical Fishing Grounds
SFZ	Statistical Fishing Zone
TPS	Tiger Prawn Season
VMS	Vessel Monitoring System

LIST OF FIGURES

LIST OF TABLES

LIST OF TABLES

CHAPTER 1
INTRODUCTION

1.1 Introduction

The theoretical and applied literature on modelling the economics of fisheries is fairly extensive. Much of this literature has focused on bioeconomic modelling, the analysis of markets for fishery products and on evaluating different fishery management strategies. Only a small proportion of the bioeconomic modelling has included a fleet dynamics submodel (Mangel & Clark 1983, 1986; Hilborn & Walters 1987; Sampson 1992; Gillis, Peterman & Tyler 1993; Gillis, Peterman & Pikitch 1995). In modelling fleet dynamics alone the discrete choice framework has been proposed (Bockstael & Opaluch 1982; Eales & Wilen 1986; Morey, Shaw & Rowe 1991; Campbell, Meyer & Nicholl 1993; Dupont 1993; Campbell & Hand 1999). In most theoretical and applied work related to the fishing process, fishing is treated as a single activity. Very little attention has been directed at describing fishing as a complex process that (i) consists of a number of inter-related activities, and (ii) is dependent on the economic behaviour of the fisher. Realistically, many fishing processes can be viewed as multistage, multiperiod reward processes that consist of searching for and harvesting a target species.

Hilborn and Ledbetter (1979), Moloney and Pearse (1979), Wilen (1979), Bockstael and Opaluch (1982), and Botsford, Methot and Johnston (1983) cover a general discussion of search in natural resource production. An extensive theoretical treatment of search in fisheries is given by Mangel (1982a, 1985b, 1989), and Mangel and Clark (1983, 1986). Allen and McGlade (1986, 1987), Campbell, Meyer and Nicholl (1993) and Campbell and Hand (1999) present empirical studies of search behaviour in fisheries. Modelling fishing as a complex process involving a series of activities is important for understanding the forces that influence the movement of individual fishers and overall fleet dynamics. Research by Mangel and Clark (1983, 1986), Mangel (1982a, 1985b, 1989) and Dorn (2001) is exceptional in its treatment of fishing since it focuses on the sequencing of the component activities in the process of fishing[1].

[1] Indeed these researchers disaggregate fishing into steaming, searching and harvesting activities. In this thesis fishing is depicted as consisting of searching and harvesting activities only.

Regardless of the observed significance of the searching and harvesting components of fishing, there is a dearth of research incorporating these components in fisheries models. Historically, biological models of fishery management have been emphasised because population dynamics have been thought to be the most limiting part of fisheries systems. Consequently, economic models have been treated as submodels of biological models of stock assessment, population dynamics and fishery management. In addition, in order for economists to account for search and harvest as distinct activities, data on the components of fishing must be of a relatively fine spatial and temporal resolution, and such data are generally not readily available.

Implicit in the exclusion of search behaviour and fleet dynamics from most bioeconomic modelling are the assumptions that catch rates are independent of the fisher's past history of temporal and spatial locations, and the choice of fishing ground is independent of past catch rates. That is, there is an implication that fishers either go where they know fish are located, or that they fish randomly. The observed temporal and spatial habits of vessels challenge this assumption. Observed spatial and temporal patterns of fishing activities are likely to reflect movements in response to catch information and opportunities, the fishers' knowledge of the history of the entire fishery system and the fishers' reaction to fishery management policies, among other things. Fishers are appropriately modelled as economic maximisers suggesting that they respond to catch per unit effort (CPUE) in different areas and are subject to fishery policy and other constraints. The concept of maximising profit is well-presented in general and in the fisheries specific literature (Gordon 1954; Weston 1954; Sandiford 1986; Ward & Sutinen 1994; Dorn 1998; Campbell & Hand 1999; Holland & Sutinen 1999; Larson, Sutton & Terry 1999; Babcock & Pikitch 2000). Fishers compare economic returns expected from alternative fishing grounds, and are likely to relocate if the expected net benefit from fishing in the current fishing ground are lower than returns realised in alternative fishing grounds. In addition, and contrary to the deterministic nature of many bioeconomic models, there is evidence to suggest that searching and harvesting are appropriately modelled as stochastic processes (Mangel 1982a; Mangel & Clark 1983; Dorn 2001).

Search patterns in a fishery are a result of individual and group interactive behaviour. An explicit model or framework for incorporating search in fisheries must, therefore, recognise individual decision making as well as group decision making. The search component of fishing is also affected by fishery management policies. The objectives of fishery managers and fishers must be identified, and the constraints faced by them must be accounted for explicitly. The importance of treating fishing as a stochastic process, and of accounting for factors that affect the decision to target a particular fishing ground, is consistent with the analysis of fisheries production by Doll (1988), the analysis of search behaviour by Campbell, Meyer and Nicholl (1993) and Campbell and Hand (1999), the technical analysis of search in fisheries (Mangel 1982a, 1985b, 1989; Dorn 2001) and the modelling of fishing as a Markov process proposed in this thesis.

1.2 The Methodology

The analytical framework developed in this thesis is based on Markov chain theory. Markov chain theory has been used extensively in fields such as labour and income dynamics (Lane & Andrew 1955; McCall 1971), forest management (Usher 1966, 1969a, 1969b), human resource management models (Hopkins 1972, 1974; Spinney & McLaughlin 1979; Bleau 1981), machine reliability models (Foster, Phillips & Rogers 1981; Shaked & Shanthikumar 1990), mover-stayer migration models (Frydman 1984), biological population models (Woolhouse & Harmsen 1987a,b; Caswell 1989), and reinforcement learning models (Surton & Barto 1998). This theory has been selected to characterise searching and harvesting based on the observation that fishery production is a stochastic, multiple-objective, multi-stage, temporal and spatial activity that reflects both individual and group behaviour. This Markovian based approach enables an *ex-post* descriptive analysis of vessel movements, and sets the basis for incorporating fleet dynamics in bioeconomic modelling. It also enables us to identify some of the likely reactions of the fishing fleet to changes in management policy, including those that affect search time, access to fishing grounds and participation.

The Markov model is based on a series of historical transition probabilities that represent movements between fishing grounds. Patterns of movement are illustrated using Markov chains and directed graphs. While not providing an explicit model of the behaviour of fishers as economic agents, it is maintained in this thesis that such behaviour is still consistent with a Markov model based on revealed vessel and fleet movement. Simulations of likely vessel movements are performed conditional on the past location of vessels. The transition probabilities reflect fishers' individual and group behaviour, subject to constraints that are peculiar to the spatial unit of fishing, and constraints that are specific to the temporal dimension of fishing. The transition probabilities give the likelihood of effort allocation at selected fishing grounds, over two consecutive time periods. The real transition probabilities indicate the likelihood of relocating to an alternative fishing ground, and virtual transitions indicate the likelihood of remaining on the current fishing ground.

The decision regarding where to fish is at the core of the transition probabilities of Markov chain theory. In most applications of the Markov model, exogenous, historical transition probabilities are used[2]. The Markov structure developed and applied in this thesis is enriched by a set of equation structures that define discrete choice in fishing behaviour. In this thesis, two extensions of the Markov model are proposed. In one extension to the basic Markov model, fishers' decisions, which are conditioned by the fishing history of all the fishers, are represented as a multinomial choice problem. The transition probabilities are modelled within a multinomial logit (MNL) choice framework. Modelling transition probabilities in this manner recognises historical transition probabilities as the outcome of the economic behaviour of fishers. The implications for fleet dynamics of fishery management can, therefore, be simulated using a Markov model enriched through updating the transition probabilities.

In the second extension to the basic Markov model fishers' ground choices are modelled as an economic process using a seemingly unrelated regression (SUR) model. The collective behaviour of fishers participating in the fishery is modelled, therefore, within the Markov process, by using both the MNL and the SUR

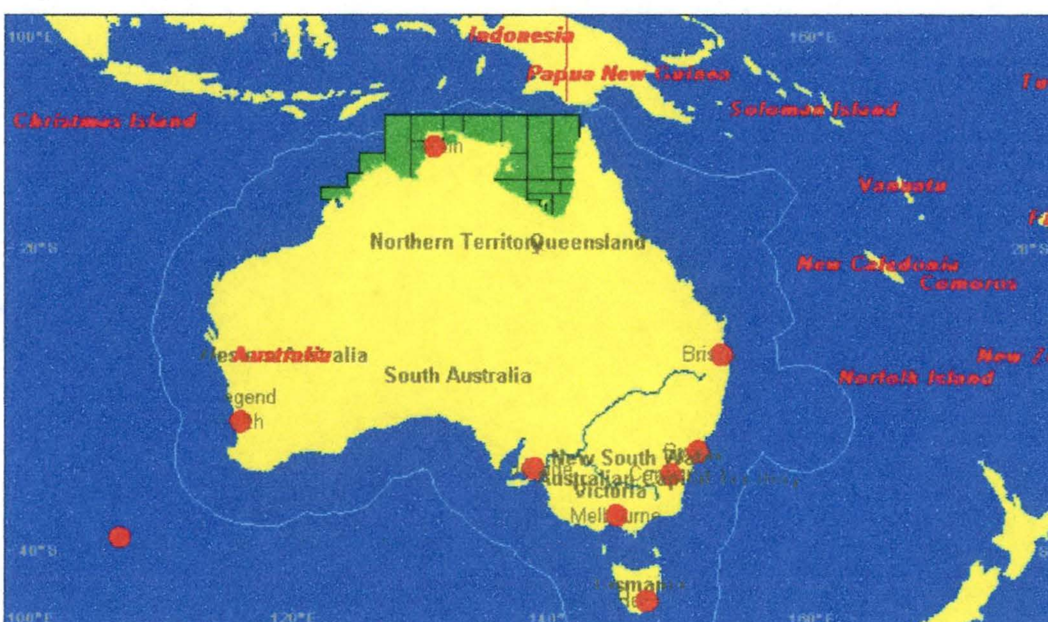
[2] Exogenous variables are those variables that cannot be explained by any of the variables used in the mode. Endogenous variables can be explained by other variables used in the expressed model.

approach. It is noteworthy that MNL and SUR are commonly used frameworks for analysing economic behaviour. Although the SUR approach is explained and results of empirical estimation are reported in this thesis, only the MNL approach is used for simulating fleet movement under different fishery management policy settings.

1.3 Australia's Northern Prawn Fishery: An Application

The case study presented in this thesis uses grid-specific effort allocation and catch data to analyse the variation in fishing patterns realised by commercial fishers in Australia's Northern Prawn Fishery (NPF). The NPF is a Commonwealth-managed fishery (Taylor 1994; Sachse & Robins 1995) and extends across northern Australia from Cape York to Cape Londonderry. It is defined as the sea area bounded by 127°E to 142°E and 10°S to 18°S (see Figure 1.1).

Figure 1.1 Location of Australia's Northern Prawn Fishery



The NPF was established in the late 1960s, and it is the most valuable capture fishery managed by the Commonwealth of Australia (McLoughlin, Staples & Maliel 1993, 1994; McLoughlin, Swallner & Maliel 1996). In 1988 the fishery generated revenue of $135 million from a catch of 7900 tonnes (Commonwealth of Australia 1989). Production in 1992-93 was estimated to be worth over $98 million from a catch of around 8000 tonnes (ABARE 1993, p.9). The gross value of production in 1997-98 was over $119 million from a catch of 8912 tonnes (ABARE 1997, 1998). The NPF is a multi-species fishery with at least nine prawn species, two species of bugs, one species of scallop, and several species of squid being taken commercially. The fishery is based mainly on the common banana prawn *(Penaeus merguiensis)*, the brown tiger prawn *(Penaeus esculentus)*, and the grooved tiger prawn *(Penaeus semisulcatus)*. These species comprise almost 80% of total annual catch (McLoughlin, Staples & Maliel 1993, 1994; McLoughlin, Swallner & Maliel 1996), and each species has different management requirements (Sachse & Robins 1994, 1995).

In the modelling of fleet dynamics it is also imperative to understand the movement of prawns during their life cycle. Research on prawn movement in the NPF has recognised that prawn larvae respond to incoming tides (Somers & Kirkwood 1984; Poiner et al. 1998; Hall & Watson 2000; Kenyon, Die & Loneragan 2000). It is, therefore, important to (i) identify the critical water depth associated with behavioural changes, (ii) identify which larvae are likely to be carried in ocean currents, and (iii) identify prawn habitats. Somers (1994b) indicates that generally

i. all of the prawn species spawn offshore[3],
ii. nursery grounds vary remarkably,
iii. growth rates vary between species (female prawns grow faster and to a larger size than males).
iv. most species are sexually mature at six months but fecundity increases with age, and
v. young prawns move offshore into fishing grounds.

The banana prawn (*Penaeus merguiensis*) is the more abundant of the two banana prawn species caught in the NPF. Adult banana prawns are found in muddy sediments in depths shallower than 20 metres. The species aggregate in schools that may contain up to 400 tonnes of prawns. These schools are located with relative ease using echosounders, and spotter planes, and their location can be

[3] Note that over 50 different species of penaeid prawns inhabit Australia's northern tropical waters, and that only nine are of commercial interest in the NPF (Somers 1994b).

marked on a GPS plotter[4]. The offshore migration of banana prawns is linked to the variation in the pattern and amount of rainfall during the annual summer monsoon (Somers 1994b, p. 56).

Tiger prawns spawn in waters 20 to 30 meters deep, and complete their early development in shallow, coastal seagrass beds. NPF tiger prawns rely on a relatively narrow, shallow belt of seagrass as their critical nursery habitat. In addition, different types of seagrass within the NPF provide different value as tiger prawn nursery habitats (Poiner *et al.* 1998). By contrast, banana prawns rely on the mangroves lining small creeks in northern Australia as their critical nursery areas. Poiner *et al.* (1998) also observed that "the failure of tiger prawn stocks to rebuild to predicted levels in recent years despite a reduction in fishing effort is that many of the young prawns produced each year may not survive to reach nursery areas"[5].

Of the tiger prawn species (the brown tiger prawns (*Penaeus esculentus*) and the grooved tiger prawns (*Penaeus semisulcatus*)), the grooved tiger prawns are found in deeper waters and on muddier substrates. The tiger prawns have two spawning seasons, and thus have two cohorts of larvae that settle in shallow seagrass and algal beds in sheltered coastal areas (Somers 1994b, p.59). Large juveniles leave the estuary and move through fishing grounds and disperse into deeper offshore waters that may be "even beyond the fishing grounds in the NPF" (Somers 1994b). The prawns subsequently move shoreward to aggregate on the fishing grounds thus forming the basis of the tiger prawn fishery (Somers 1994b, p.59). It is also noted that no specific environmental factors are known to stimulate the movement of prawns although both tiger prawn species are known to move in response to a drop in salinity Somers (1994b, p.61).

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[4] A plotter is an electronic device, also called a navigation plotter, GPS plotter or a navigation chart plotter, that houses charting software and shows the position of a vessel with reference to land and sea masses. The primary functions of a plotter are (i) the viewing of electronic charts, (ii) the storage of electronic information about specific locations and events, (iii) the editing of routes, and updating of coloured-coded records of locations and events.

[5] Poiner *et al.* (1998) noted that (i) only certain critical areas of the adult fishing grounds produce the next generation of tiger prawns; (ii) prawn larvae from these areas are transported in favourable currents to inshore nursery grounds, and (iii) larvae produced too far offshore, or in areas that have unfavourable currents, are lost.

The adult banana prawns (*Penaeus merguiensis*) are found mainly over muddy sediments in depths shallower than 20 metres (Somers 1994b, p.56). The adult red-legged banana prawns (*Penaeus indicus*) are found offshore in depths ranging from 45 to 85 metres which is much deeper than the distribution of the white banana prawn (*Penaeus merguiensis*) (Somers 1994b, p.57; Hall & Watson 2000). In addition, although the red-legged banana prawns do not form schools to the same degree as white banana prawns (*Penaeus merguiensis*), they nonetheless aggregate (Somers 1994b, p.57).

The brown tiger prawns (*Penaeus esculentus*) are found in shallower waters ranging from 10 to 30 metres, and sediments with lower mud content. The grooved tiger prawns (*Penaeus semisulcatus*) are found in deeper waters, and on muddier substrates than the brown tiger prawns (*Penaeus esculentus*).

The endeavour prawns (blue endeavour prawn - *Metapenaeus endeavouri* and the red endeavour prawn - *Metapenaeus ensis*) are caught in depths between 30 and 50 metres. The substrates that red endeavour prawns inhabit are generally muddier than those inhabited by the blue endeavour prawn.

Little is known about the biology of the two king species; namely, the blue-legged or western king prawn (*Penaeus latisulcatus*) and the red-spot king prawn (*Penaeus longistylus*). These two species of king prawn comprise only a modest part of the catch in the NPF. The blue-legged king prawn tend to inhabit shallow sand or mudflats, or even seagrass beds (Somers 1994b). The red-spot king prawns (*Penaeus longistylus*) are known to inhabit coral reefs (Somers 1994b). Adult king prawns are generally caught in sandy areas of the western and southern Gulf of Carpentaria (Somers 1994b, p.63).

The account given above suggests a movement of prawns to and from fishing grounds. These migrating patterns have not been captured in the thesis. A full account of prawn movement in the NPF would benefit understanding of fishery immensely. The assumption made in this thesis is that, at the point of harvesting, given the relative harvesting speed of vessels and the temporal and spatial allocation of fishing effort, the prawns are stationary. This assumption of prawn movement is based on research literature by Somers and Kirkwood (1984), Hall and Watson (2000), and Kenyon, Die and Loneragan (2000). For example, Kenyon, Die and Loneragan (2000) conducted preliminary analyses of migration and movement of adult, red-legged banana prawns in Joseph Bonaparte Gulf (JBG) and noted that the range of prawn movement in Joseph Bonaparte Gulf is fairly limited (Kenyon, Die & Loneragan 2000)[6].

Management policy for the NPF is formulated by the Northern Prawn Management Advisory Committee (NORMAC), its membership representing industry, management and research. Mainly the scientists of the Division of Marine Research, Commonwealth Scientific Industrial and Research Organisation (CSIRO) have provided the greater part of advice on stock assessment for the NPF. The NPF has been managed using limited entry controls since 1977. A management structure based on units of fishing capacity was introduced in 1984. The existing complex set of input controls that include gear restrictions, as well as time and area closures, was introduced in 1987 (Commonwealth of Australia 1989, p.4).

Fishers in the NPF make decisions regarding the allocation of effort amongst the various stages of the fishing process subject to a range of biological, technical, environmental, economic, institutional and fishery management constraints. Understanding both the way in which these decisions are made and being able to explain the dynamics of the fleet is important for fishery management because it can assist in evaluating fishers' and fleet reactions to management policies. This is particularly important in the NPF where there have been several fleet restructuring programs (Sachse 1991, 1992; Sachse & Robins 1993, 1994; Pownall 1994; Robins & Sachse 1994a, 1994b) in an attempt to reduce the size of the fleet and the level of fishing effort. Generally, fleet restructuring has failed to reduce effort due to "technology creep". The efficiency of fishing vessels has increased due to advances in technology. This technology creep (Robins & Sachse 1994a, 1994b) increases the effective effort of the fleet (Robins, Wang & Die 1996, 1998), and

[6] Note that JBG is part of the Management Zone (MZ) outlined in Chapter 3, and that fleet dynamics in the JBG also affect fleet dynamics in the NPF. In addition, red-legged banana prawns form about 10% of the catch of the NPF (Robins & Somers 1994).

has implications for fishers' effectiveness in searching for the target species in the NPF.

The current management framework of the NPF lacks an explicit model of individual search and harvesting behaviour, and fleet movement, which can be integrated with available stock assessment and fishery management models. So part of this thesis involves using the theoretical Markov based framework to (i) describe the movement of vessels in the NPF, (ii) explain search and fishing patterns in the NPF, (iii) forecast likely vessel movements in the NPF, and, (iv) show how the Markov modelling framework can be used to simulate the effects of changes in management strategy and policy. The fishery management strategies examined are confined to the shortening of the length of the fishing season and to specific area closures. Data limitations mean that the policy simulations reported in this thesis are illustrative.

1.4 Specific Objectives of Thesis

The specific objectives of this thesis, therefore, are as follows:

- Review the literature on search that may be used in a fisheries context.
- Review the background of the NPF, highlighting variables that are important for understanding fleet dynamics in that fishery.
- Develop a theoretical framework for describing fisher behaviour that accounts for the sequential, multistage nature of commercial fishing.
- Use the theoretical framework to forecast likely movement of vessels in the NPF.
- Simulate likely vessel movements in the NPF given selected management policy changes.

1.5 Significance of Thesis

The research presented in this thesis is significant for the following reasons. First, it develops a theoretical framework that accounts for the nature of fishing as a sequential, multistage and multiperiod stochastic activity. This framework captures important aspects of the fishing process and also explicitly models the behaviour of fishers. In this regard, this thesis effectively fills gaps in the literature by providing a framework for including fisher behaviour in fishery management models. The Markovian framework is shown to be appropriate for this purpose as it treats fishing as a series of activities over time and space. However, in this thesis the basic Markovian approach is enriched through use of MNL and SUR models of individual and group behaviour. This offers researchers the ability to model transition probabilities as the outcome of economic processes. The resulting framework, therefore, has the additional strength of being multidisciplinary.

Second, developing the theoretical framework required an extensive review of the search literature. Discussion of this literature within the context of fisheries search represents a useful contribution to the fisheries management literature.

Third, the thesis represents a first attempt at modelling economic behaviour in fishing in the NPF, and illustrates a way in which search theory and quantitative analysis of management can help inform fishery policy makers. Fishery managers are often unable to forecast or simulate future fleet movements, or to predict what the fleet's response will be to a change in fishery policy. The motivation in this thesis is to develop a framework which managers can use to describe, forecast and simulate fleet dynamics. The present thesis accomplishes this purpose. The empirical component of the thesis shows how quantitative techniques, including the link to the Markov framework, could be useful in guiding management decision making in the NPF. In addition, the framework is (i) consistent with the observed spatial, temporal, sequential and multistage nature of the fishing process, (ii) consistent with the observed nature of fishers' decision making (as economic maximizers), and (iii) is practical for forecasting and simulation purposes.

Finally, the thesis evaluates similarity of fleet movements in different fishing periods using selected characteristics of transition probability matrices. Assessing similarity in this way has not appeared in the Markov modelling literature before. An evaluation of the similarity of fishing periods is important since forecasts of fleet movement can be made on the basis of characteristics of similar fishing periods.

1.6 Plan of thesis

The rest of this thesis is structured as follows. A review of the general literature on search that may be useful in understanding search in fishing is presented in Chapter 2. Chapter 2 also reviews the economic literature on search and fleet dynamics in fisheries.

A review of the background of the NPF focusing on variables that are important for developing an understanding of fleet dynamics in Australia's NPF in Chapter 3 presents the historical development of the NPF and describes the history of management policy in the fishery. Chapter 3 also includes a description of the data set that subsequently forms the basis of the study of NPF fleet dynamics in Chapters 5 and 6.

A theoretical framework based on the Markov model for describing and forecasting vessel movement is developed in Chapter 4. Chapter 4 includes detailed explanation of a basic Markov model as well as the MNL and SUR models of individual and fleet level behaviour.

In Chapter 5, the Markov framework developed in Chapter 4, is used to describe and explain fleet dynamics in Australia's NPF. Characteristics of transition matrices and estimates of MNL and SUR models are presented.

In Chapter 6 the forecasting of the movement of fishers in the NPF is presented. These forecasts are evaluated using selected quantitative techniques. Selected fishery management strategies in the NPF are evaluated using both ordinary Markov procedures and a simulation procedure in which transition probabilities are updated on the basis of postulated MNL estimates. In particular simulations of likely vessel movements conditional on ground closure and season shortening are presented.

Chapter 7 presents concluding remarks on the main findings and policy implications arising from the thesis. The major contributions of this thesis are outlined and future directions of research are suggested. In addition, the main limitations of the research presented in this thesis are highlighted.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

The objective of this chapter is to review the literature on search relevant to fisheries analysis. The literature review is presented as follows. Following the introduction, Section 2.2 deals with the general theory of search and its origins in natural and social science systems. Section 2.3 reviews how search has been modelled in the literature, and in particular, presents the technical aspects of the search process. Fisheries fleet dynamics and the allocation of effort in fisheries are presented in Section 2.4. The theoretical and empirical models on fleet dynamics and the allocation of fishing effort are then presented in Section 2.5. The models outlined in Section 2.5 are compared and contrasted in Section 2.6. Concluding remarks are drawn in Section 2.7.

2.2 Origins of Search Theory

Search theory is concerned with the gathering, updating and optimal use of information (Mangel 1985a, 1985b, 1989). The origins of search theory as detailed by Koopman (1956a, 1956b, 1957, 1980) concern military planning and implementation, and the literature contains, therefore, extensive applications to military activity (Koopman 1980). The application of search theory has since spread to several non-military areas such as mineral exploitation (Cozzolino 1972; Mangel 1983), economics (Lippman & McCall 1976), fisheries (Mangel 1982a, 1985a, 1989; Meyer 1992), marketing and management (Lippman & McCall 1979), and industry and medicine (Haley & Stone 1980).

Important aspects of search that are addressed in the literature include sequential search (Dobbie 1963), problems of optimal control (Isaacs 1965; Gal 1980; Hajeck 1975), well-known search patterns (Kohn & Shavell 1974), general search theory (Stone 1975; Washburn 1980, 1981; Discenza & Stone 1981; Richardson 1989), game theory, differential games and statistics, optimal search density, paths, patterns and games (Chudnovsky & Chudnovsky 1989a, 1989b; Gal 1989; Stone 1975, 1989). Modern accounts of search theory are presented by Stone (1975, 1989) and Mangel (1985b, 1989). The theory of search is focussed generally on finding optimal search plans. Solutions to a range of search problems may function as decision aids in planning and executing searches over space and time.

2.3 Modelling Search and the Technical Aspects of the Search Process

The search for any selected target can be modelled as a process of sampling from a probability distribution of the target (Stigler 1961, 1962; Mangel & Clark 1983, 1986; Quirk 1986; Ruffin 1988; McTaggart, Findlay & Parkin 1996). The pattern of search for any of these targets can be described as sequential[1] (McCall 1970, Stahl 1989) or non-sequential (Manning & Morgan 1982). Searchers can search optimally if informed reliably about the probability distribution of the targets, otherwise a search is postponed and searchers gather additional information. It is often assumed that the probability distribution of the targets is known (Cross 1980; Kohn & Shavell 1974), although studies on optimal search from unknown probability distributions are also documented (Rothschild 1973, 1974; Cross 1980)[2]

The general objectives of searchers given in the search theory literature include finding the joint density for target location and unsuccessful search, locating the optimal search tracks, finding the optimal effort allocation, identifying the target of interest in the shortest possible time, and/or, maximising the probability of detection subject to constraints imposed on the amount of search effort (Richardson 1989).

A number of technical aspects must be addressed in any particular search problem. These are (i) the probability of detection, (ii) effectiveness of search, (iii) target motion, (iv) allocation of search effort, (v) use of search technology, (vi) learning, and, (vii) stopping rules. These seven key technical aspects of the process of search are discussed in Sections 2.3.1 through 2.3.7 respectively.

[1] In sequential search the economic agent samples one information source at a time and decides whether to stop or continue sampling.

[2] Under strict conditions, optimal search rules from unknown distributions have the same qualitative properties as rules for search from known distributions (Rothschild 1973, 1974).

2.3.1 Probability of Detection

The probability of detecting a target is often given in the form of a detection function. The functional form depends on the characteristics of the targeted species and the type of search tactic used (Kadane 1971). Stone (1975) and Mangel and Clark (1983) have suggested that the time between the detection of targets is exponentially distributed, and that the parameters of the detection function, in particular the reward, may also be associated with other distributions such as the gamma distribution. The form of the detection function has implications for optimal search. Stone (1975), for example, showed that a uniformly optimal search plan will be optimal either when the detection function is concave, or the search space and search effort are continuous.

In making assumptions about target motion in fishery applications it is quite important to consider the biology of the species targetted (see Section 1.3). For example, in the NPF nine species of prawns are targetted (see Section 1.3). These species inhabit fishing grounds of different depth and substrate composition as detailed in Section 1.3. Depending on the technology used in search (see Section 2.3.5) the probability of detection will depend, therefore, on the fisher's knowledge of the fishing grounds which in turn will influence the effectiveness of search (see Section 2.3.2) and facilitate learning from search.

2.3.2 Effectiveness of Search

The effectiveness of search depends mainly on the initial purpose of search and on how well the objective of the searcher is met. For example, search may be intended to establish the location of the target only, with no further action intended. This type of search is called detection (location or whereabouts) search (Kadane 1971; Stone & Kadane 1981). In detection searching the searcher develops an optimal detection search plan or pattern among all cells exclusive of the cell with the highest *a priori* target location probability. In the case where a search problem involves moving targets, the optimal search plan may be found by solving a finite number of optimal detection search problems for each cell in the grid (Stone & Kadane 1981).

In cases where search is intended to establish the location of a target and action is taken, search is called surveillance search[3]. Surveillance search problems are generally far more complex than detection search problems. Richardson (1989) suggested that the allocation of search effort in detection or surveillance searching should minimise expected entropy. Entropy is used as a measure of the effectiveness of search, and the effectiveness of searching may be captured by evaluating the extent to which search enlarges the information matrix available to the searcher. The effectiveness of search can, therefore, be evaluated on the basis of whether detection or surveillance has been accomplished successfully.

2.3.3 Target Motion

Assumptions about target motion have considerable influence on the characterisation of the search process and search plans. Search problems have been formulated for targets whose movement can be characterised as diffuse (Hellman 1970, 1971), stochastic (Brown 1980), non-Markovian (Mangel 1981) or Markovian (Tierney & Kadane 1983). Most search problem studies have concentrated, however, on stationary objects (Pollock 1970; Dobbie 1974; McCabe 1974). Generally, search problems involving non-stationary targets are more difficult computationally than search problems involving stationary targets (Dobbie 1975). Because of this complexity, the tendency has been to convert a search problem for a moving target to a stationary target equivalent in order to obtain solutions (Stone & Richardson 1974). Other techniques (Brown 1980; Mangel 1982b, 1989) have, however, provided elegant solutions for non-stationary search problems. In spite of these advances in the analysis of problems involving search for non-stationary targets, cases exist where no effort allocation function satisfies the necessary conditions for optimal search plans (Richardson 1989). The existence of optimal search plans for moving targets is, therefore, not necessarily guaranteed.

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[3] Features of surveillance search problems and the necessary conditions for optimality of search when the target motion is Markovian are discussed by Tierney and Kadane (1983).

Knowledge of prawn species biology, in particular prawn movement, is important (Somers & Kirkwood 1984; Somers 1994a,b; Hall & Watson 2000; Kenyon, Die & Loneragan 2000). In fisheries applications of the concepts of target motion summarised in Section 2.3.3, it is important to note that in the case of prawn movement in the NPF, the target species is assumed to be stationary during harvest (Somers & Kirkwood 1984; Somers 1994a,b; Hall & Watson 2000; Kenyon, Die & Loneragan 2000).

It is common to assume that a constant proportion of prawns migrate from one fishing ground to another at the end of a selected time step (Hall & Watson 2000, p.216). In addition, in modelling exercises migration rates are often assumed equal across fishing grounds and across months (Hall & Watson 2000, p.217). The target prawn species is modelled as a stationary target since the average trawling speed in the NPF[4] is faster than the movement of prawns within a fishing ground. In particular, the incidence of daily fishing effort and the nature of fishing in the NPF, justify the treatment of the target species as a stationary target.

2.3.4 Search Effort

The type of search pattern used by a searcher depends on the type of search effort employed. Generally, two types of search effort problems can be observed. These are discrete and continuous search effort problems[5]. In discrete search effort problems the target is assumed to be located in several cells and the searcher looks for the target in a sequence of discrete looks or glimpses. The looks may be dependent or independent, and each cell has a prior probability of containing the target. In continuous search effort problems, the target may be located in cells, as in the case above, or in Euclidean n-space. Search effort is, however, measured such that it is infinitely divisible (Stone 1975; Richardson 1989)[6]. Koopman (1957) made an early

[4] Based on my personal observation and communication with skippers and gear technologists the average trawling speed appears to be about 3 knots.
[5] The distinction between discrete and continuous effort search problems is highlighted by Chew (1967, 1973), Matula (1965) and Richardson (1989).
[6] That is, search effort can be located as finely as necessary over the entire search space (Stone 1975; Richardson 1989).

expression of a search problem involving continuous search effort. Richardson (1989) details solutions to continuous effort search problems[7].

2.3.5 Searcher's Technology and Movement

The technical aspects of search discussed above have concentrated entirely on target behaviour with no attention given to the interaction between the searcher and the target. Searchers may react to the characteristics of the targeted resource and/or the resource manager, or their behaviour may be independent of both. In cases where searcher activity is dependent on target behaviour, it is important to consider searcher-target interaction.

One key feature of the searcher that is important in solving search problems involving searcher-target interactions is the sweep width of the technology the searcher uses[8]. The sweep width of a sensor is defined as the area under the lateral range. The definition of the sweep width requires, therefore, that a lateral range function be specified. The lateral range of a search path is the range at the point of closest approach to a target. The definition of the sweep width requires the assumption that the search sensor approaches a stationary object at a constant speed along a long straight path, and that this search path begins well beyond the maximum detection range of the sensor and continues past the target to a point well beyond the maximum detection range[9].

The sweep width of a sensor often varies over the search region due to factors such as environmental conditions (for example, poor visibility), weather and climatic factors, the care the searcher is exercising in searching, and possibly, the target's change of location or state over time. The sweep width and movement of the searcher

[7] An extensive treatment of continuous effort search problems involving Euclidean n-space are given by Dobbie (1963) and Stone (1975).

[8] The technology's ability to store information from searching and capturing is also important. For example, the use of Global Positioning Satellite (GPS), differential GPS (DGPS), plotters, logbooks and personal diaries, facilitates recording of search tracks and associated net rewards.

[9] The function defining the probability of detecting the target when the sensor's path has a specified lateral range is called the lateral range function of the sensor. Negative lateral ranges indicate that the target is to the left of the sensor track

may also alter the detection function. It is, therefore, common to specify a sweep width and time-dependent detection function (Stone 1989).

The major assumption required for the sweep width and time dependent detection function is that search effort is distributed randomly over the search area according to a uniform distribution, and that each small increment of search effort is positioned independently of the past search effort. Stone (1989, p.17) noted that there are no examples of search situations that truly satisfy this assumption, but nonetheless commended the use of the exponential function for its computational convenience and because the function provides a reasonable lower bound for the detection function for a wide class of search problems.

In the case of searching and fishing the use of GPS, echosounders and plotters[10], for example, yields information on substrate, composition and location of fishing grounds, and facilitates recording of past successful search and fishing. Such knowledge of the sea-bottom is important to fishers since the mapping of the sea-bottom, in conjunction with catch data, can be used to identify habitats of targetted species, as well as lead to an assessment of fishing conditions.

2.3.6 Learning from Search

Search theory has been used by economists to explain and model job-search behaviour (Feigin & Landsberger 1981; Benhabib & Bull 1983; Gal, Landsberger & Levykson 1981), and consumers' product search behaviour (Rothschild 1974; Rosenfield & Shapiro 1981; Stahl 1989). In these and other applications emphasis has been placed on locating the relevant probability distribution of targets (Stigler 1961, 1962; McCall 1970) and on analysing the effect of information in reducing uncertainty in search. Within this framework, search behaviour is often modelled as sequential decision making under uncertainty (Dobbie 1963, 1968; Kohn & Shavell 1974; Rothschild 1974). The notion that searchers learn from the probability distribution of targets as they search is also introduced in this framework (Rothschild

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[10] The full colour display and generally user-friendly software make plotters quite useful for storing loads of information that fishers collect from the bridge (through general observation) and also electronic scientific information collected by other navigation or experimenting devices in the vessel.

1973, 1974). For example, it is assumed that consumers and job searchers learn about the probability distribution of prices and wages that they face. These economic agents value the outcome of searching in their economic optimisation problem as search information enables agents to update their net benefit expectation. Learning and decision-making are emphasised as key elements of the search process.

The process of learning involves an updating of prior beliefs as search occurs. The Bayesian approach to the updating of prior beliefs is commonly taken in the search literature (Rothschild 1974, Mangel 1983; Mangel & Clark 1983, 1986). The emphasis on information acquisition and processing, and Bayesian updating has become especially important in natural resource management (Mangel 1982a, 1985b, 1989; McDonald & Hanf 1992a, 1992b; McDonald & Smith 1995). The approach emphasises the role of subjective probabilities and the revision of opinion in the light of new information (Antle 1983).

The searcher is assumed to be unaware of the exact nature of the probability distribution of targets. The search process is used to obtain reliable estimates of the parameters of the probability distribution of targets. In order to update in a Bayesian manner the searcher must (i) list all possible spatial and/or temporal distributions of targets, (ii) characterise all such possibilities within a sufficiently general family of distributions, (iii) set parameters for this family of distributions, and (iv) calculate how parameters should be updated in the light of search evidence. The number of parameters involved is clearly often large and modelling all possibilities correctly is complex. The searcher uses, therefore, the best information available at the time, and their economic behaviour is consequently optimal[11].

2.3.7 Stopping Rules

Search models are generally based on the existence of a probability distribution of targets. The searcher is modelled as attempting to establish an optimal search rule. In addition to the requirement of a probability distribution of targets, searchers must

[11] Hey (1982) argues that the complexity of the search problems makes optimal economic behavior impractical. According to Hey (1982), the searcher might, therefore, be assumed to behave suboptimally.

establish a search rule for determining when the search process should be terminated. In other words, there should be a stopping rule or rule-of-thumb that the searcher obeys. It is reasonable to maintain that the rule-of-thumb varies among searchers. Furthermore, it can be argued that stopping rules will condition the searcher's method of choosing the best target, the searcher's assessment of whether a better alternative can be found easily thereafter, and the cost of continuing search.

Stopping rules have been applied to different sets of search objectives, information sets about unexamined alternatives and search costs. The literature suggests that search decisions in general and sequential search decisions in particular require a range of stopping rules. The range of stopping rules must be consistent with the assumption that underlies the searcher's set of objectives in the search process (Morgan & Manning 1982, 1985; Karni & Safra 1990).

Many stopping rule rules have been developed in economics and operations research. It is argued in the literature that stopping is based on a process of making inferences about the probability distribution of targets, the time available for search, and the quality of the alternative targets encountered. Generally, the stopping rule must be based on an empirical parameter that is unique to both the search and the nature of the search problem. In addition, it is likely that this parameter will not be determined *a priori* since searchers' preferences are unique to the probability distribution of targets and/or the probability distribution of net rewards.

In the theory of reasonable search developed, discussed and illustrated by Hey (1981) and Simon (1985), searchers are assumed to employ reasonable search rules rather than optimal search rules. Hey (1981) and Simon (1985) argued that optimal search may be highly inefficient in that it would take a large number of observations to modify the searcher's initial beliefs about the actual distribution of choice elements. Hey (1981) contends that the main problem in analysing search problems is that the search problems encountered and the related stopping rules used by the searcher have become so technically complex that technically optimal stopping rules have become impractical. Optimal stopping rules for such complex search problems may be unrealistic models of the actual search processes in the sense that some of the search models are too complex for the searcher to solve the objective function even though they may still be technically feasible. Hey (1981) argued that it is reasonable, therefore, that searchers behave as if they are solving the search problem regardless of the structure of the problem. If it is impossible to behave optimally and unwise to behave suboptimally, searchers are likely to behave reasonably. According to Hey (1981), reasonable stopping rules present more realistic and practical ways of describing search behaviour and may be better focussed than optimal stopping rules.

2.4 Allocation of Fishing Effort

A fundamental economic aspect of many production processes that is frequently ignored is the information gathering activity involved when the level of the resource is uncertain. Searching for schools of fish is an example of an economic activity that uses information collected over time and space. Explicit modelling of search in fisheries production has been relatively recent (see Paloheimo 1971; Shotten 1973; Haywood & Haley 1975; Clark 1980; Mangel 1981, 1982a, 1983, 1985a, 1985b, 1989; Swierzbinski 1981; Mangel & Clark 1983; Mangel & Beder 1985; Mangel & Plant 1985; Meyer 1992; Campbell, Meyer & Nicholl 1993; Campbell & Hand 1999; Dorn 2001). The ways in which search theory has been applied to fishers' search behaviour in these studies have been diverse (Huppert 1979; Hilborn & Ledbetter 1979; Hilborn 1985; Watson, Die & Restrepo 1993). These researchers have made an important contribution to the understanding and application of search theory in fisheries. Nevertheless, few studies have concentrated on the endogenous allocation of effort in fish production[12] in spite of evidence that search generally incurs a major transaction cost (Hempel 1969).

There is, therefore, a paucity of research on the role of search in the endogenous allocation of fishing effort. In addition, there is no evidence of an explicit model of the obvious link that exists between the allocation of fishing effort and fleet dynamics. This limitation is one focal point of this thesis. In this thesis search is

[12] The work by Mangel (1982a), McDonald and Smith (1995) are exceptions. These researchers consider fishing effort as an index of inputs.

considered part of the allocation of fishing effort that leads to spatial and temporal fleet dynamics. In linking search in fisheries and fleet dynamics, it is necessary to characterise search in fisheries in terms of the technical aspects of search discussed in Sections 2.3.1 through 2.3.7.

There are several sources of uncertainty in a fishery production system. For example, fishers are often uncertain about the relative density of fish in various fishing grounds, the effect of current fishery management policies, and/or the short and long-term effects of current fishing practices on future levels of fish stock. The short and long-term profitability of commercial fishers is likely to depend on fishers' ability to process and distribute search and harvesting information. The early detection of viable fishing grounds and/or the choice of such fishing grounds, for example, has productivity effects, and hence, profitability implications for fishers and fishing firms. Fishers who take longer to determine their optimum site configurations and optimum allocation of search effort are expected to perform less favourably.

Fishers generally have a choice of fishing locations. Fishers must decide which fishing ground to visit next, what time to visit, how long to search and when to exit the fishing ground. Fishers' economic choice of fishing locations can be described as sequential decision making under uncertainty. Discrete choice modelling can be used to emulate how decisions are made with respect to where fishers will go (Caulkins, Bishop & Bouwes 1986; Adamowicz, Jennings & Coyne 1990; Morey, Shaw & Rowe 1991; Campbell & Hand 1999; Holland & Sutinen, Smith 1999)[13].

The allocation of search effort can be used to explain both the rate of and characteristics of the search. The probability that a fishing firm will undertake search or fishing within a given time period is assumed to be a function of benefits, costs, psychological factors and past mobility (Campbell, Meyer & Nicholl 1993; Campbell & Hand 1999). Fishers are assumed to be aware of their valuation of the expected marginal costs and expected marginal benefits of search. Their valuations of

[13] Although these models use individual data and address part of sequential search in production exceptionally well, they are nonetheless not easily integrated with other models used in the analysis of behavior.

expected marginal cost and expected marginal benefit are the main part of the stopping rules in fishing strategies, search planning and execution. The use of the marginal revenue (MR) or marginal benefit (MB) rule to guide the allocation of effort from one fishing ground to another requires an understanding of efficiency in harvesting and searching. The switching behaviour of fishers, between fishing grounds, is motivated by the comparison of expected marginal benefit (EMB) and expected marginal cost (EMC). Because of the complexities of temporal and spatial search, it can be hypothesised that adopt the simple reasonable economic rule of search behaviour[14].

The theory of sequential search concerns the fundamental aspect of continuous sampling and sequential decision making. In sequential search, continued searching is profitable for economic agents if the expected benefit from search exceeds the expected cost (Gotz & McCall 1983). In the case of fisheries search, search effort is deployed to achieve a set of broad multiple objectives, such as the improvement of long run earnings, the reduced annual variations of income (Huppert 1979), maintaining CPUE at a level higher than the average CPUE or some reservation CPUE (Hilborn & Ledbetter 1979; Hilborn 1985; Allen & McGlade 1986), and decreasing uncertainty about fish location and population size.

2.5 Theoretical and Empirical Work on Fisheries Search and Fleet Dynamics

In this section a summary and review of key research on fisheries search and fleet dynamics is presented. The major contributions are by Mangel (1982a), Mangel and Clark (1983, 1986), Allen and McGlade (1986), Campbell, Meyer and Nicholl (1993), Russell and Alexander (1998), Campbell and Hand (1999), Gaertner, Pagavino and Marcano (1999), Gillis (1999), Holland & Sutinen (1999), Larson, Sutton and Terry (1999), Smith (1999), and Pelletier and Ferraris (2000). Research by Mangel (1982a), and Mangel and Clark (1983, 1986) provide a fairly rigorous treatment of the theoretical issues in fisheries search and effort allocation. Allen and McGlade (1986) and Campbell, Meyer and Nicholl (1993) present an empirical

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[14] The use of the economic rule obviates the need to make the distinction proposed by Hey (1981).

evaluation of effort allocation and search behaviour. Russell and Alexander (1998), Campbell and Hand (1999), Gaertner, Pagavino and Marcano (1999), Gillis (1999), Holland and Sutinen (1999), Larson, Sutton and Terry (1999), Smith (1999), and Pelletier and Ferraris (2000) present empirical evidence on fisher behaviour.

2.5.1 Renewal Theory of Search and Fishing

Mangel (1982a) focussed on: presenting a framework in which to define and interpret search effort using harvest (logbook) data; studying the effects of search and harvest on population estimates of fish; testing the sensitivity of long-run catch to search rates and harvest capabilities; evaluating the effects of a population of fish and depletion of stock during fishing and search operations; showing how biological and operational parameters affect long-run catch; and, presenting a study of the effects of fishers' code groups[15] on search effort and catch rates.

Mangel (1982a) modelled the process of searching and harvesting in commercial fisheries and their effects on population estimates as a renewal process. The skipper is assumed to estimate the initial catch rate and then vary the search rate in order to maximise the net value of catch. Decisions made by the skipper in the process of searching-fishing-...-searching are aimed at achieving this objective. The mean rate of encountering a school depends on fish movement (movement of schools), fish biology and operational aspects of fishing (search rate, harvest abilities), but is independent of the size of the school of fish. The distribution of fish is unknown, and the fish schools are assumed not to interact.

Mangel (1982a) assumed that the operational aspects of fishing may be characterised by the random search model proposed by Koopman (1980). The searcher is assumed to search an area that can contain only one school of fish, at a specified velocity, using a vessel of known sweep width. The mean rate of encountering schools is then estimated using the central limit theorem for the renewal process proposed by Karlin

[15] Code groups are collections of skippers that cooperate in locating fish and/or trading or sharing information on location and/or abundance of the fish stock.

and Taylor (1975). The probability of false detection of a school of fish is also introduced[16].

The model advanced by Mangel (1982a) meets the mathematical requirements proposed by Neyman (1949). The simulated data requirements for the model used by Mangel (1982a) included the following: mean time between sightings of schools; non-fishing time in a fishing operation; sweep width of vessel used by the skipper; search area that can contain only one school of fish; the number of schools encountered in a selected time interval; time spent or set time in fishing period; the number of boats searching and fishing competitively or cooperatively, and the correlation between detection capabilities of boats.

The simulated data are used in the following manner. First, the expected value of the number of schools encountered is calculated by applying the equation for the long-run rate of harvest likely to result from a specified set time. This is used to draw inferences on catch and effort. Second, the sensitivity of the expected value of the number of schools to the detection rate and fishing effort for different values of the probability of detecting a false school is shown. Third, an estimate of the number of schools present using the likelihood of observing a specified number of schools is provided. Fourth, the probability of at least one member of a code group encountering a school of fish is estimated. Finally, the effects of depletion are demonstrated.

In modelling the effect of a finite number of schools on search, Mangel (1982a) shows the dependency of expected harvest on fishing effort and the expected value of the number of schools. The main results drawn suggest that the first-order CPUE is independent of the population of the fish stocks. Second-order CPUE increases with increases in population of the stock and the expected value of the catch and, decreases as fishing effort increases. The equation structure used by Mangel (1982a) suggests that the number of schools encountered seems more sensitive to changes in search ability and technology than to changes in harvest rates (Mangel 1982a, p.363).

[16] Note that skippers are assumed to stop searching and attempt to harvest the false school.

For large populations, CPUE is roughly independent of the population size and decreases as effort increases, if the rate of encountering schools is modelled as a gamma density. The effects of search ability and technology on population (stock size) depends therefore, on effort effectiveness.

2.5.2 Information, Uncertainty and Updating in Fisheries Search

Mangel and Clark (1983) focussed on demonstrating the relative benefits accruing from cooperative and competitive search strategies. They also show how to determine the optimal allocation of search effort across several historical fishing grounds, while ascertaining whether fishers who are acting competitively will be motivated to allocate searching effort in an approximately optimal manner, or whether a cooperative (or regulated) solution would be more productive. Mangel and Clark (1983) find an optimal allocation of search effort over time under competitive and collaborative search while modelling the general simplifications of the searching process in a real fishery and investigate how fishers make rational decisions on where to search for fish.

In modelling uncertainty regarding the location of fish concentrations, and the effect of search by fishing vessels in reducing such uncertainty, Mangel and Clark (1983) started from the premise that fishers must make their decisions on the basis of the best information available to them at any given time. Mangel and Clark (1983) adopted the standard Bayesian approach to the continual updating of past fishing information. In this approach fish abundance estimates are updated by a Bayesian formula, after a preliminary period of fishing, and vessels may then be reallocated according to the results.

In the Mangel and Clark (1983) model fishers determine the allocation of vessels in order to maximise the expected net return using the most recent updates. The objective function is maximised assuming: a time-to-end of fishing period or the number of remaining periods of fishing is stipulated; that updating of probabilities occurs only after the first fishing period and that vessels are then reallocated to their final destination for the remainder of the season; that the cost of initial allocation is independent of their destination and thus can be ignored; and, that current abundance of fish on each ground is unknown, but the probability distribution for abundance (the so-called *a priori* probability distribution) for each ground is known from the historical record of catch and effort.

The data requirements for the model proposed by Mangel and Clark (1983) included data on fishing time period, fishing areas, number of vessels searching within a specified area, total number of vessels licensed to fish in the fishery, number of schools of fish encountered during the search period, total number of schools of fish that can be encountered, costs of switching from one fishing site to another, fixed costs of sending a vessel to a fishing ground, and cost per unit time of operating a vessel on the ground[17]. The data and the model were used to compute the level of benefits accruing to individuals updating under competitive or cooperative search strategies, under the following conditions: non-random search; imperfect information about fish location; search in which targets re-group; and non-uniform school sizes.

Mangel and Clark (1983) also investigated the sharing of information between fishers and argued that it is likely that an over-concentration of fishers in one fishing ground may displace the fish concentrations through fishing activities. As a result catch rates may be reduced with each drop of the net. In this regard, too many fishers in a given fishing ground may spoil the fishing ground. Mangel and Clark (1983) concluded that there is, therefore, an incentive to limit the number of fishers sharing information on the location of shrimp concentrations.

Mangel and Clark (1986) analyse the behaviour of fishers in an uncertain environment, especially when new types of regulations are being considered. They show how the fishing process produces the physical catch and information about the stock level and assess the likely impact of the utilisation of information by fishers. The model proposed by Mangel and Clark (1986) involves a set of differential equations to model detection and movement of single and multiple targets. The searcher is modelled variously as maximising the probability of detecting a single

[17] The latter are the variable costs.

target in a fixed time period, minimising the time to detect a single target, and maximising the total number of targets detected in a multi-target search problem. The searcher's optimisation problem can be considered as one, or a combination, of these objectives. The search problem or model of searching is generalised to that of the optimal allocation of search effort over several periods. The probability of detecting the target is updated regularly, in a Bayesian fashion, as the searcher accumulates information.

The data requirements for the model include data on the area of the fishing region, the search rate, the search time, the total number of cells in search space, the number of objects detected in a selected time interval, the number of discoveries occurring in an operation of specified duration, the position of the target, the total number of fishing trips, number of vessels targeting a particular fishing ground, total number of vessels licensed to fish in the fishery, and the cost of sending a vessel to a selected ground for one trip. The data and model are used to accomplish three fundamental tasks (i) to find the optimal number of vessels in a fishing ground, (ii) to show the effect of depletion and competition, and (iii) to show the effect of regulation on commercial fishing patterns.

2.5.3 Relative Attractiveness of Fishing Grounds

Allen and McGlade (1986) argued that fishers could be classified into groups, namely high risk takers and low risk takers. The choice of fishing grounds in which fishers reside depends on the quality of information exchanged, groups of fishers residing in different fishing grounds, the estimated attractiveness of the respective fishing grounds, as well as basic mimicking behaviour. The model proposed by Allen and McGlade (1986) takes into account the fishers' decisions to switch between species and fishing grounds according to their relative expected yields or catch rates. This search model is built on an equation structure that defines or describes the dynamics of the fish population at different fishing grounds as they spawn and multiply (as they would do naturally without human intervention); the distribution of fish in reaction to fishing; the movement of fishers in response to information they have about catch rates being realised by the fleet fishing in the area; and, the movement of the fish and fishers across fishing grounds.

In developing the model Allen and McGlade (1986) argue as follows. Each skipper is attracted to fish in a particular zone according to the relative attractiveness of that zone as perceived by the skipper and each skipper weighs the expected return that can be obtained from the reported catch and species-mix in a fishing ground against the cost of transferring to another zone and the distance of that zone from the home or closest port. Additionally, fishers switch in and out of fisheries depending on the abundance of species available in other fisheries and the relative profitability of fishing different species in different fishing ground.

Allen and McGlade (1986) suggested a framework for measuring the relative attractiveness of a fishing ground. This attractiveness is proxied by the number of boats visiting and staying in a selected fishing ground. In short, the rate of change of boat participation in a fishing ground is computed and compared to the expected rate of change in boat participation. The model by Allen and McGlade (1986) is built, therefore, on the premise that the spatial and temporal distribution of species and the relative return (profitability) of different species in different fishing grounds drive the allocation of fishing effort which generates the catch. This premise was also outlined and detailed earlier by Mangel and Clark (1983). The model proposed by Allen and McGlade (1986) requires data on variables on stock abundance, recruitment and biomass variables, and economic variables such as the profitability of fishing.

2.5.4 Differences in Fleet Search Strategies

Campbell, Meyer and Nicholl (1993) examined the Doulman (1987) hypothesis on differences in fleet search strategies[18]. The researchers focussed on examining and comparing the spatial distribution of two fleets, testing the hypothesis that vessel movement is responsive to catch rates, analysing the success of fishers in locating

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[18] This hypothesis suggests that differences in modes of operation of fleets may be due to differences in the structure of their respective fishing industries.

schools of tuna and the relationship of this success rate to the number of vessels involved; modelling skipper behaviour as a Bayesian updating of information and, examining the process of information sharing associated with the spatial and temporal distribution of vessels.

Campbell, Meyer and Nicholl (1993) tested the hypothesis that skippers relocate in response to catch (Hilborn & Ledbetter 1979) by applying an Almon polynomial lag model to the relationship between the number of vessels in a fishing area and the value of the catch per vessel in previous periods. The number of vessels in a sub-zone, during a fishing week, is expressed as a function of the lagged average value of catch per vessel in the sub-zone[19]. The model is estimated initially for American (US) and Japanese fleets in each sub-zone. The observations for both fleets are then pooled and the model estimated with dummy variables for the fleet categories.

A maximum likelihood estimator based on a method by Beach and MacKinnon (1979) is used to correct for autocorrelation due to the inclusion of the lagged independent variable. The clustering of vessels of a selected fleet is deduced from inspecting recorded quarterly set positions for the vessels in the two fleets. These recorded set positions are assumed to be random and from a Fisher distribution.

Campbell, Meyer and Nicholl (1993) divided the fishing zone (the Economic Exclusive Zone) into sub-zones and performed an analysis of variance to test for preferences for particular areas or zones by either fleet. Quarterly log-book data on position of set, type and time of set, number of unsuccessful sets, catch by species and length of fishing trip are required for the model. The data are used in the model to accomplish three primary tasks: (i) calculate the number of sets made by a particular group of vessels in a subzone during a quarter; (ii) support a regression analysis that tests the hypothesis that information is disseminated more quickly and completely in the Japanese fleet than among the American vessels; and, (iii) show that if revenue maximising vessels are moving in response to information about catch

[19] Note that the equivalent term for fishing ground used by Campbell, Meyer and Nicholl (1993) is sub-zone. The aggregation of sub-zones defines the Economic Exclusive Zone (EEZ).

rates, the number of vessels in an area should be positively related to the value of catch per vessel in previous periods in that area.

2.5.5 Modelling Fisher Behaviour

In recent literature it is recognised that studies on fisheries dynamics and stock assessment have traditionally focussed on the resource and excluded the fisher component (Ward & Sutinen 1994; Campbell & Hand 1999; Holland & Sutinen 1999; Pelletier & Ferraris 2000). Accounting for fisher dynamics (i) is useful for improving the evaluation of the impact of a fishery on the corresponding resource, (ii) can serve to build a model of the dynamics of a mixed fishery, and (iii) can be useful to quantitatively assess the consequences of management measures on stock dynamics (Pelletier & Ferraris 2000).

The common theme in most recent fishery management literature is that fishery managers 'manage' fishers, and that fisher behaviour should be studied (Ward & Sutinen 1994; Russell & Alexander 1998; Campbell & Hand 1999; Gaertner, Pagavino & Marcano 1999; Gillis 1999; Holland & Sutinen 1999; Larson, Sutton & Terry 1999; Babcock & Pikitch 2000; Mistiaen & Strand 2000; Pelletier & Ferraris 2000; Smith 1999; Smith 2000; Dorn 2001). These studies have made efforts to model fisher behaviour or classify fishers according to their fishing tactics (Russell & Alexander 1998) or fishing strategies[20]. Most notable in the recent literature is the use of fine-scale data as well as qualitative information from interviewing fishers (Russell & Alexander 1998), and the conceptualisation of fishing as a series of related decisions (Babcock & Pikitch 2000; Dorn 2001).

It is also recognised that target species may change in the course of the year, and for a given target species, the gear used and fishing location may also change in relation to the spatial and seasonal dynamics of corresponding populations (Pelletier & Ferraris 2000). It is imperative, therefore, to note that fishers' knowledge of fish behaviour is important in the design of fishing strategies (Gaertner, Pagavino &

[20] The difference between fishing tactics and fishing strategies has also been noted (Pelletier & Ferraris 2000).

Marcano 1999). The modelling of the migratory behaviour of species is important (Eiler 2000; Gunn & Young 2000; Hall & Watson 2000; Hancock, Smith & Koehn 2000; Kenyon, Die & Loneragan 2000; Punt 2000; Punt & Cui 2000; Walker et al. 2000) and should, therefore, complement studies on fisher behaviour. In the analyses of the behaviour of fishers it is common to treat schools of fish as stationary (Gaertner, Pagavino & Marcano 1999; Hall & Watson 2000; Mills et al. 2000)[21]. Other studies (Deriso, Punsly & Bayliff 1991; Heifetz & Fujioka 1991; Punt & Cui 2000) have, however, focussed on Markovian movement of pelagic species.

In this section, the empirical evidence on fisher behaviour by Russell and Alexander (1998), Campbell and Hand (1999), Gaertner, Pagavino and Marcano (1999), Gillis (1999), Holland & Sutinen (1999), Larson, Sutton and Terry (1999), Smith (1999), and Pelletier and Ferraris (2000) is reviewed. The review focusses mainly on the general method used, type of data needed, and the findings presented.

Russell and Alexander (1998) focussed their research on obtaining statistical support for the hypothesis that different fishing strategies or skippers' skills partly account for variability of fishing success within a fleet. To test this hypothesis, Russell and Alexander (1998) selected a technologically underdeveloped mixed species tropical seine fishery in south central Luzon, Phillippines. In this fishery boat size is similar, skippers do not have formal navigational training, and boats are not equipped with electronic fish-finding gear, and/or mechanised hauling of gear. Russell and Alexander (1998) reviewed the quantitative and qualitative evidence for different fishing strategies in the fleet and examined the degree to which these strategies account for differential fishing success. These researchers collected data on daily catch weight and composition, the prices received, the fishing location chosen, the number of trips made, the type of gear used, and the characteristics of buyers of the fish product. Cluster and discriminant analyses were used to assign skippers to several subgroups representing distinct fishing strategies. In addition, multiple regression was used to assess the efficiency (mean catch per trip) of vessels. The

[21] It is my observation that this assumption is valid if (i) the relative movement of the school is far lower than the movement of the harvesting gear, and (ii) the analysis of fleet movement and species movement is at a very fine-scale and at a specific point during the harvesting process.

results of the study suggested that (i) boat size is not a significant variable in explaining total catch, (ii) the cost of a boat and gear (even when depreciated), or the size of the engine fail to correlate with total catch, and (iii) the number of crew, fishing grounds visited per fishing period and species targetted per fishing period significantly affect the efficiency of vessels. Russell and Alexander (1998) concluded that (i) the differences in seining strategies can be identified through a measure of choice of fishing location, the number of trips made, and the types of species caught per time period, and (ii) knowledge of fleet strategies that influence fishing success is critical for forming policies for preserving a biologically sustainable level of fishing effort.

Campbell and Hand (1999) presented qualitative choice models of location choice for United States (US) purse-seine vessels. A multinomial logit model and a nested logit model were applied. Using logbook data on fishing location, species catch and composition, number of days fished, and the number of sets made, Campbell and Hand (1999) focussed their model mainly on grid specific fleet dynamics. The results from the study suggest that (i) skippers consider both expected revenues and the cost of moving when selecting fishing grounds, (ii) skippers are more likely to select fishing grounds farther from port, (iii) the nested logit model of spatial allocation effort performed better that the non-nested model in predicting fleet movements, (iv) information about the distribution of the resource is based partly on historical patterns of ground choice, water temperature (indexed by the Southern Oscillation Index), and the amount of search undertaken, and (v) the sharing of catch rate information among the US fleet is common.

Gaertner, Pagavino and Marcano (1999) used logistic regressions to model the influence of Venezuelan skipper's behaviour on the catchability of surface tuna schools. The researchers noted the general absence of logbook data on different aspects of fishing behaviour, and used at-sea observer data on different aspects of fishing behaviour. In the empirical study Gaertner, Pagavino and Marcano (1999) focussed on factors affecting (i) the decision to chase a school, (ii) the decision to launch a net, and (iii) the success of the set. The range of factors identified included factors linked with (i) fisher's skills and efficiencies, (ii) the fishing equipment of boats, (iii) the resource and (iv) the environment. The study provides empirical evidence on how catchability can be affected by interactions among fisher decisions, the gear used and an understanding of fishing behaviour. Any model designed to analyse fisher behaviour must, therefore, have embedded such key features exposed by Gaertner, Pagavino and Marcano (1999) and other researchers on fleet dynamics.

Gillis (1999) examined vessel interactions and long term temporal trends in catchability in the Scotian Shelf silver hake (*Meluccius bilinearis*) fishery using spatial and temporal data collected for the purpose of regulating the fishery. The aim of the study was to examine "how regulatory data can be used to investigate aspects of fish and vessel behaviour that are relevant to the interpretation of catch and effort statistics but difficult to study directly". The data set used included information on vessel characteristics such as (ownership, length, tonnage), catch composition, gear configurations, initial and final positions, initial and final times of each trawl[22]. Trawl location and time were used to generate estimates of trawl linearity - defined as the nature of the course followed by the vessel. Trawl linearity was then used as a proxy for fine-scaled temporal and spatial fleet dynamics. The results from this study suggest, among other things, that (i) vessel interactions are significant in the silver hake fishery, (ii) the profitability of trawls was slightly greater when local vessel density was higher, (iii) concentrations of fishing activity indicate additional periodicity beyond that due to diel effects, and (iv) mean catch rates vary significantly among vessels.

Holland and Sutinen (1999) focussed their research on an empirical examination of individual fisher's choice (i) a fishery, and (ii) a fishing location. Using trip data for over 400 large trawlers fishing in New England, Holland and Sutinen (1999) used a discrete choice random utility model to model fisher's choices of fisheries and fishing areas. Their model of expected utility is based on the literature (see Bockstael & Opaluch 1983; Eales & Wilen 1986; Dupont 1993; Ward & Sutinen 1994) and on ethnographic interviews with skippers of large trawlers. In addition, a generalisation

[22] It is noted that no quantitative information on vessel interactions was provided.

of the multinomial logit model (the nested logit model) is used to estimate fishery or location choice[23].

The model proposed by Holland and Sutinen (1999) used data on catch rates, average revenue, vessel characteristics (tonnage, length, horsepower, age), steaming time, surface area of a given fishery or fishing area, among other factors. In addition, "lagged average revenue rates for different alternatives and individual vessel's past behaviour" were used to predict the choice of species groups and fishing location on a trip-by-trip basis. The model is used to (i) explain the behaviour of individual fishers and (ii) predict aggregate effort levels in different fisheries and areas over time. The resultant individual-level behavioural models are used to predict aggregate temporal and spatial fishing effort distribution for the overall trawler fleet.

The empirical results of the model suggest that: (i) fishers tend to follow their own historical patterns of fishery and location choice; (ii) fishers have developed time- and location-specific information that increases their expected revenues by decreasing time spent searching for aggregations of fish, (iii) most fishers move between areas and fisheries frequently as relative conditions change, (iv) fishers do not seek to reduce risk by choosing fishing areas where revenue rates are less variable, (v) higher effort levels may increase the chance that a fisher would have acquired information about conditions in a fishing area, (vi) "given a reduction in revenue expectations in a particular area within a zone, fishers may be more likely to move to a different zone or species than to move to an area within the same zone where catch expectations are generally low at that time of year", and (vii) a fishers' experience in particular areas and fisheries impacts of their propensity to fish in those areas in the future.

[23] Holland and Sutinen (1999) noted that the nested logit model accommodates cases where the random component for groups of alternatives may be correlated.

Larson, Sutton and Terry (1999) focussed their research on discrete choice modelling of fisher participation in the multispecies trawl fishery of the Bering Sea/Aleutian islands region off Alaska. In their empirical assessment of fisher behaviour, a random utility model framework is used to explain fishers' ground and species choice. The fisher's main objective is taken as maximising the expected utility of quasi-rent from participating in the fishery. Nonparametric estimates of operation-specific moments, namely, the conditional mean and standard deviation of quasi-rent, by fishery and week are used to explain probabilities of choosing different target species. The data used by Larson, Sutton and Terry (1999) included data on catch volume and composition, and weekly net returns to fishing[24]. The results of the study suggested that (i) fishers are sensitive to risk and generally tend to be risk averse, (ii) seasonal effects on the choice of species are significant, and (iii) the information hypothesis dominates the congestion hypothesis[25].

Smith (1999) presented a model for a probabilistic analysis of decision making about fishers' trip duration by recreational (sport) fishers in the Strait of Georgia, British Columbia. The aims of the study were to (i) estimate catch rates and their variance, (ii) define a unit of effort for the fishing fleet, (iii) assess if fisher skill affects fishing success, (iv) assess if fishing success affects the length of a daily boat trip, and (v) evaluate the effectiveness of daily bag limits in reducing catch per daily boat trip.

Smith (1999) produced bivariate probability mass distributions for the proportion of boats in a fishing fleet that quit fishing. This proportion of boats is expressed as a function of catch and effort. In the model, catch rates are related to (i) the probability that a boat trip ends after a certain number of fishing hours, and (ii) the effect of fishing success on the probability. The probability of catching a certain number of fish after a certain number of fishing hours, and the probability of ending an a fishing trip are expressed as a function of time and fishing success (Smith 1999, p.961).

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[24] In the study by Larson, Sutton and Terry (1999) there is no information on (i) costs of switching gear, and (ii) fishery-specific switching costs.

[25] Note that variables such as weekly earnings and costs identified in the study by Larson, Sutton and Terry (1999) have not been available for the NPF. If collected, the can be used in the MNL Markov or SUR Markov framework.

The model developed by Smith (1999) to capture the dynamics of a fleet of boats making daily fishing trips, therefore, requires the following data: target species, the number and type of fishing gear, the catch rates, and time expended targeting exclusively a particular species.

Although the effects of time, currents, time of day, fish distribution, and choice of boat can contribute to the overall variability in fishing success, such specific factors were not included in the empirical evaluation of the model proposed by Smith (1999). These variables are important since a boat trip can also end for reasons other than fishing success, such as the need to accommodate personal and domestic responsibilities of fishers.

The results of the study by Smith (1999) suggest that (i) the number and type of fishing equipment significantly influenced the length of a boat trip, and (ii) the number of fishers on board did not affect the length of a boat trip. The responses of fishers to fishing success will depend, therefore, on the characteristics of particular fishers, the magnitude of the daily bag limits (DBL), and the fisher's propensity to reach the DBL.

The study by Pelletier and Ferraris (2000) was focussed on an approach to determine fishing strategies using commercial catch and effort data for a large-scale Celtic Sea groundfish fishery, and a small-scale Senegalese fishery. The model used by Pelletier and Ferraris (2000) included a combination of multivariate descriptive methods such as factorial analysis and classification techniques. The results suggested that, in general, each fishing tactic is strongly characterised by a single target species. Tactics used for a target species might differ by fishing locations and/or time of year.

2.6 Comparing and Contrasting Models

The models of fleet behaviour reviewed in Section 2.5 suggest that economic and noneconomic conditions determine the manner in which fishers react to different fishing conditions and regulations. This view is reinforced by Watson, Die and Restrepo (1993). In most of the work on fleet dynamics, fishing effort has been assumed to be constant throughout the year. It is likely, however, that in the event of seasonal closure, total annual fishing effort would be either maintained or reduced proportionally to the closure length. In addition, search and harvesting have been treated as discrete events on the assumption that search activities can be clearly distinguished from harvesting activities.

For virtually all areas surveyed in search theory, search information is incorporated by means of Bayesian analysis. Fishers' search behaviour is viewed as a response to Bayesian updating of information. The spatial and temporal allocation of effort is modelled by analysing the skippers' preference for certain statistical fishing grounds. Fishers' relocation decisions are partly in response to catch returns, and partly the success rate of other vessels in terms of locating and catching schools of fish.

The literature reviewed above suggests the following key points are important in modelling fleet dynamics. First, fisheries search is an important determinant of fleet location behaviour. Fishers' search decisions are shaped by perceived search costs and benefits. Fishers' uncertainty about cost and benefit are likely to influence their decisions on whether and how to undertake an initial search. Second, search for fish concentrations can make up a significant proportion of the cost of fishing operations. An efficient search process can lead to lower harvesting costs and greater returns. Third, information sharing can lead to efficiency benefits. The benefits of information sharing are eroded, however, as the fleet size increases. Finally, fishing strategies are species-dependent, fishery-specific and are related to an array of objectives of fishers and fishery management.

2.7 Concluding Remarks

The literature selected for review in this Chapter suggests that search is important in the allocation of fishing effort. The importance of understanding the technical aspects of the search process detailed in Section 2.3 is highlighted. These technical aspects are probability of detection (section 2.3.1), effectiveness of search (section 2.3.2), target motion (section 2.3.3), search effort (section 2.3.4), searcher's technology and movement (section 2.3.5), learning from search (section 2.3.6) and stopping rules (section 2.3.7); and, they play a significant role in the planning, implementing and managing of search in fisheries.

Fishers are expected to learn from searching by updating their search beliefs in the light of information collected, and modify their search plans and strategies. It is clear from qualitative research by Russell and Alexander (1998) that even in less technologically advanced fisheries the highly ranked skills of a successful skipper[26] are knowing (i) where to find the schools of fish, (ii) how to read the current and movement of waves, (iii) where and when to set the gear, and (iv) the geography of the sea-bottom. In this ordering, knowledge of the sea-bottom was the fourth most important feature. In technologically developed fisheries the use of data observed and stored by the fisher (a skipper at a bridge) is important in formulating the fisher's belief, and thus influences location choice (Smith 2000). A significant amount of information sharing occurs (Allen & McGlade 1986; Wilson 1990; Sampson 1992; Russell & Alexander 1998), and different intra-fleet strategies tend to influence fishing success[27].

Fishers are expected to apply decision rules that guide them in assessing the optimality of any chosen strategies. In addition, fishers are expected to react to current management policies. In their spatial and temporal allocation of effort, fishers will choose from a set of fishing grounds and relocate in response to their catch rates and information about fishing conditions elsewhere.

The concentration of effort exerted by each fisher on a selected set of fishing grounds will depend mostly on the fisher's catch history, fish behaviour, knowledge of the fishing grounds and other related economic variables. It is important, therefore, in analysing commercial fishing patterns to examine the participation of individual vessels and the entire fleet, and the ground choices that fishers make.

[26] Russell and Alexander (1998) interviewed fishers in order to elicit a rank ordering of skipper skills.
[27] Although useful to assume that fishers learn from the resource, the environment and activity of other fishers, it is also important to note that Ward and Sutinen (1994) suggested that fisher behaviour in the Gulf of Mexico shrimp fishery is not influenced by stock variability.

The theoretical and empirical research reviewed in Chapter 2 indicate that the components of the fishing process can be represented as a renewal process, with fishers allocating their effort in a manner that maximises the expected net return. In Chapter 3 a background to the Australian NPF is presented. This sets the scene for using selected statistics to examine catch rates in specific fishing zones and fishing grounds, and to report the level of participation and ground choice in the fishery. A framework that describes the process of fishing as a Markov process with rewards and allows for explaining ground choices and simulating fleet dynamics under selected fishery management policies, is presented in Chapter 4.

CHAPTER 3

COMMERCIAL FISHING PATTERNS IN THE NPF

3.1 Introduction

The purpose of this chapter is to provide some background on Australia's NPF with an emphasis on those variables which are important for understanding fleet dynamics in this fishery. This chapter documents observed commercial fishing patterns in the NPF and is used as a foundation upon which an analytical framework for analysing fleet dynamics in the NPF based on Markov chain theory is built. This analytical framework is developed and explained in detail in Chapter 4. The Markov framework and its related supporting models rely on data on transitions and catch rates. In this chapter, therefore, the background to the NPF is given in terms of fishers' observed allocation of effort, transitions to selected fishing grounds, the catch of targeted prawn species and management implications of fleet dynamics. Spatial and temporal activity patterns of commercial fishers in the NPF are discussed in the sections that follow.

A chronology of the development and management of the NPF is detailed in Section 3.2. An account of the process of fishing in the NPF is presented in Section 3.3. Fishers' search strategies and patterns are described in Section 3.4. A description of the data set is given in Section 3.5. This is followed in Section 3.6 by a descriptive analysis of fishing patterns in the NPF. The descriptive analyses include results on vessel characteristics, fishers' ground choice and vessel movement. A summary of a model proposed by Robins, Wang and Die (1996, 1998) for measuring the fishing power of vessels in the NPF is presented in Section 3.7. The implications of fishers' ground choice and vessel movement for the spatial and temporal allocation of effort, or fleet dynamics are highlighted in Section 3.8. Concluding remarks are drawn in Section 3.9.

3.2 The Chronology of the Development and Management of the NPF

The chronology of the development and management of the NPF presented in this section refers to selected data on catch and fishing effort for the period 1970 to 1995. The NPF catch and effort data are collected from prawn trawlers that fish between Cape York (Queensland) and Cape Londonderry (Western Australia). Catch and effort for the Kimberley Prawn Fishery (KPF) in Western Australia are also collected. Annual data on catch and effort during the period 1970 to 1995 are presented in Table 3.1 below[1].

Fishing for prawns in the Gulf of Carpentaria began in 1954. The vessels that fished in the Gulf of Carpentaria were based in Karumba. By 1959, extensive commercial development of the fishery had commenced. Up to the mid-1960s there was minimal management of the fishery, with vessel operators expected only to hold State and Commonwealth fishing boat licences. In 1967 a Japanese research vessel recorded commercial-sized prawn stocks in Joseph Bonaparte Gulf. The presence of international vessels prompted the establishment of Australian patrols set up to protect Australian interests in the fishery.

In 1968 the Australian government introduced a fishing plan for northern waters designed to control foreign involvement and to achieve rapid but sustainable growth in the NPF. A total of 65 boats were reported landing prawn product. By 1969 a total of 144 boats were participating in the fishery. Most of these vessels were small wooden trawlers with ice boxes or brine tanks. Motherships were introduced in 1969.

As a result of growing concern over possible overfishing limits on fishing effort were proposed. The first area closures in the NPF were imposed in 1969, and involved no fishing in Queensland waters of the Gulf of Carpentaria during January, February and March and a complete ban on trawling in Queensland rivers flowing into the Gulf of Carpentaria. These area closures were aimed at protecting juvenile banana prawns[2].

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[1] In the empirical analysis that follows in this thesis, the focus is on predicting fleet movement using daily data collected for the fishing periods 1991 through 1994.

[2] Restrictions on net mesh size and headrope length were also applied at this time.

Table 3.1 NPF Statistics (Catch, Effort and Boat Numbers 1970 to 1995)

	Catch by Prawn Species Group (tonnes/annum)					Fishing Effort	
Year	All Species	Banana Prawn	Tiger Prawn	Endeavour Prawn	King Prawn	No. of boats	Boat days
1970	3 257	1 702	1 138	417	0	191	7 859
1971	8 948	7 364	1 183	400	0	169	11 628
1972	6 654	4 801	1 380	472	0	180	11 707
1973	6 492	4 226	1 672	594	0	217	12 279
1974	13 815	12 711	666	434	4	196	10 976
1975	4 583	3 160	973	444	6	107	11 371
1976	6 319	4 519	1 118	657	5	145	13 989
1977	10 398	6 345	2 900	1 125	28	193	18 930
1978	7 456	2 535	3 599	1 240	82	237	24 318
1979	10 300	4 775	4 218	1 213	94	240	25 119
1980	9 964	2 835	5 124	1 891	111	269	38 985
1981	13 400	5 672	5 559	2 073	95	286	43 419
1982	11 036	3 875	4 891	2 124	144	271	41 707
1983	9 831	2 382	5 751	1 488	207	254	41 407
1984	10 095	3 770	4 525	1 714	83	252	38 379
1985	9 811	4 469	3 592	1 671	77	231	33 462
1986	6 451	2 935	2 682	748	85	238	33 801
1987	8 713	4 257	3 617	772	65	234	30 432
1988	7 591	3 381	3 458	669	81	222	32 919
1989	9 636	5 466	3 173	909	85	223	34 475
1990	6 636	2 221	3 550	735	128	200	30 569
1991	11 554	6 605	3 987	879	81	172	27 259
1992	6 267	2 254	3 084	880	47	170	26 921
1993	7 572	4 292	2 515	733	35	127	22 318
1994	6 263	2 157	3 162	872	72	128	23 547
1995	10 294	7 961	4 125	1 150	58	125	21 721

Source: ABARE (1999)

By 1970 over 190 boats were participating in the NPF. Echosounders and spotter planes were used in the search for banana prawn and for gathering information. In addition, radar and spotter planes were used to track movements of other vessels in the fleet. Catches increased dramatically. Vessel operators (skippers) widened their fishing area. The technical and gear aspects of fish finding and capture were modified considerably. For example, steel freezer trawlers with higher catching and carrying capacities and snap-freezing facilities were introduced. Twin, triple and quad trawl rigs were used. The total increase in fishing effort in the NPF was estimated at between 20 and 30 percent (Robins & Sachse 1994a).

In the early 1970s, CSIRO scientists advised that the banana prawn fishery was fully exploited (Somers 1994). The Gulf of Carpentaria Prawn Closure Committee formed, and seasonal closures were introduced to protect the banana prawn stock. In 1972, several fishing grounds were closed to all forms of trawling. It is generally believed that the ground closures protected juvenile banana prawns. A ban on daylight fishing also encouraged night fishing in the tiger prawn fishery.

New and larger prawn trawlers entered the NPF in 1973 when the Commonwealth Government introduced a bounty payable to shipbuilders for the construction of new ships. The bounty had adverse effects on the fishing industry since it altered the fleet structure of the NPF considerably. This increased capitalisation in the fishery and led to a record catch of over 13 000 tonnes of prawns in 1974. However, processing facilities were unable to handle the large amounts of prawn product. Most of the prawn product was dumped, the quality of prawns was reduced and prices were lower. At this time a cooperative approach to managing the NPF was adopted.

The Northern Fisheries Committee was formed, and a Working Group from this Committee concluded that: banana prawns were fully-exploited, and tiger prawns were under-exploited; that mid-March was the appropriate time to start the season, and that over-capitalisation could occur with the increasing numbers of larger, steel, freezer trawlers (Robins & Sachse 1994a, 1994b, 1994c). The Working Group also recommended improvements to storage and transport facilities in an attempt to overcome dumping and wastage of banana prawn product.

In 1975 banana prawn catches fell to unprofitable levels, and the fleet moved towards targeting tiger prawns. In 1976 a total of 145 licences were endorsed for the NPF.

Catches of tiger prawns increased considerably in the period from 1976 to 1980. The NPF moved from a mainly banana prawn fishery to a tiger prawn fishery. Limited entry and a like-for-like boat replacement policy were recommended. A three-year interim management plan started on 1 January 1977. The Northern Prawn Fishery Advisory Committee (NORPAC) was established. This Committee represented a formal involvement of industry in fishery management.

Fishing effort increased sharply in 1977 when 193 vessels received endorsement to participate in the fishery. Most of these vessels were large, efficient trawlers and had high participation rates. The main management policies in place were the declaration of a Management Zone managed under limited entry, a boat replacement policy and a continuation of seasonal closures for banana prawns.

During the late 1970s, try-gear became a standard item of equipment in fishing operations in the NPF. Most wheelhouses were equipped with an automatic pilot, radar, echo sounders, and at least two radios. By 1980 the tiger prawn was the main targeted species. Trawlers and fishing strategies were modified, and scientists and marine resource managers' research activities were refocussed. For the first time annual tiger prawn catch exceeded 5 000 tonnes. The fishery was considered to be both fully-exploited and over-capitalised (Robins & Sachse 1994a, 1994b; Somers 1994).

The interim management plan was revised and a new boat replacement policy was introduced. The policy allowed for like-for-like replacement of larger boats and increases in the length of smaller boats. Licence fees were also increased to fund research and management, and fishers remained obligated to complete logbooks. It was also observed that limited entry had not been effective in limiting over-capitalisation; the capacity and power of trawlers had increased, boat participation rates had risen, and the skippers' ability had increased substantially (Robins & Sachse 1994a, 1994b).

In 1982 the Australian Fisheries Council recognised the problem of excess fishing capacity in the NPF. A review of methods of controlling fishing effort was initiated. Boat units were used as the basis for the boat replacement policy. A voluntary buy-back scheme funded by industry levies was introduced. Permanent and seasonal closures were continuously reviewed (Somers 1994b).

In 1984 the Northern Prawn Fishery Management Committee (NORMAC) was established. The advisory powers of this Committee were increased substantially, and Class A and Class B boat units were redefined. In 1985 CSIRO scientists considered the stocks to be over-exploited and recommended a reduction of fishing effort on pre-spawning stocks. User-pays policies for management of Commonwealth fisheries were introduced[3].

In the mid- to late- 1980s new otter-board designs were introduced into the fishery. These designs were aimed at reducing drag and thus reducing fuel consumption. Satellite navigation systems were introduced, but were later superseded by Global Positioning Satellite (GPS) systems whose accuracy and precision revolutionised navigation and fishing operations.

In 1986, 238 boats fished in the NPF, and prawn catches were very low. A 30 percent reduction in effort was recommended. To effect this reduction before the next tiger prawn-spawning season, a four-month total closure was introduced. In addition, provisions of the boat replacement policy requiring the surrender of some units on replacement were introduced.

[3] Initially industry paid 40% of the cost of management, but this increased to 90% by 1990. Costs were expected to rise to 100% in 1994-95.

In 1987 NORMAC agreed on a list of measures for reducing effort and fleet capacity in the longer term. These measures included: a reduction in the number of Class-A units; extending the mid-season and end of year closures; banning daylight fishing in selected parts of the NPF; placing further restrictions on fishing gear[4], and a more restrictive boat replacement policy.

By 1992 a compulsory reduction of 30.8 percent of fishing effort was still required by 1 April 1993. In 1993 a total of 127 trawlers fished in the NPF. Class A units were further reduced. This compulsory reduction of units attracted legal action with fishers demanding compensation for their losses. Several fishing effort restrictions were relaxed. For example, net-size restrictions were removed. The limit of two nets per vessel was retained, however. The mid-year closure was shortened by two weeks (Pascoe & Whitman 1995). The ban imposed on daylight trawling in areas west of Oxley Island in the Northern Territory, during the tiger prawn season was lifted.

In 1995 the Northern Prawn Fisheries Management Plan was implemented and the Northern Prawn Fishery Advisory Group (NPFAG) recommended a 25 percent reduction in fishing effort by 1999. The end of year closure was brought forward to 7 November 1997. However, in 1998 NORMAC abandoned the 1997 season closure. Instead, a partial area closure of the principal tiger prawn grounds for the entire month of November was trialed. The measure of gear Statutory Fishing Rights (SFRs) was also altered in order to achieve a 15 percent reduction in total gear towed by a vessel. In 1999 NORMAC acknowledged that the lifting of the 1997 season restrictions and their replacement with area closures had failed, and fishing effort in the tiger prawn fishery was 35 percent above the level associated with maximum sustainable yield (MSY).

In response, NORMAC extended the mid-year and end-of-year closures. Evidence submitted to the Senate Review Committee in 2000 suggests that fishing effort in the

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[4] Twin gear was allowed in 1987. The maximum net sizes were a 14-fathom headrope length for trawlers with more than 375 Class A units and a 9-fathom headrope length for trawlers with 375 Class A units and less.

tiger prawn fishery still exceeds the recommended level by 35 percent and that the level of effort creep has been between 2.5 and 5 percent per annum since 1988 (Robins, Wang & Die 1996, 1998).

The history of the management of the NPF suggests that the policies implemented have not been successful in terms of reducing landings and effort in the NPF. A possible reason is that the spawning stock and recruitment relationship is too complex, is misunderstood and/or is not documented fully[5] while the daily catch rates are declining, indicating poor recruitment (Vance, Staples & Kerr 1985). Furthermore, the two main tiger prawn species may not come from a single stock within the bounds of the NPF as commonly assumed, and should not be managed, therefore, as one stock (Wang & Die 1996, p.88). It may well be that fishers have not changed their fishing patterns in a significant way, that the economic behaviour of fishers in the NPF has not been understood fully, or that the effects of the policy on fleet dynamics was wrongly anticipated.

3.3 The Process of Searching and Fishing in the NPF

Commercial harvesting of prawns in the NPF can be characterised by a joint production function, with two 'goods' namely tiger and banana prawns. Fishers may implement one of two possible strategies. First, fishers may choose to harvest either banana prawns or tiger prawns throughout the season. Second, fishers may choose to harvest banana prawns through some part of the season and then switch to tiger prawns. The harvesting of tiger prawns is a low risk activity compared to the harvesting of banana prawns. In modelling fisher behaviour, in this thesis, risk is simply construed in terms of the fisher's uncertainty of harvest level in the NPF. The banana prawn fishing period is quite short and prawn fishers can take up to 80% of the stock within the first week of fishing (Somers 1994b).

[5] Future recruitment depends on the level of uncaptured stock at the end of the fishing season. If the number of adults is unknown, and their reproduction not predicted reliably, then recruitment cannot be predicted reliably. Failure to predict recruitment reliably has implications for estimation of biomass available in the forthcoming fishing season.

Diligent, daily maintenance of vessels and gear, and focussed searching and harvesting strategies are, therefore, more critical in the banana prawn fishery than in the tiger prawn fishery. There is greater flexibility the tiger prawn fishery in terms of the capacity to cope with incidental interruption in search and harvesting. One can argue, therefore, that the point at which fishers switch to tiger prawns during a fishing season will depend on the relative risk associated with harvesting the two species and the revenue differential. This switch-point can be identified in at least two ways. First, one can trace the time path of market prices or the value of banana and tiger prawns catch throughout the fishing season. Second, the time variation of relative returns to banana and tiger catches can be estimated. Information about other factors such as the catch in other fisheries, may be crucial in guiding the decision to fish for both or only one species of prawns. In general, it is argued in this thesis that relative abundance or catch rates of the two species is the main decision variable in this *switching game*. This argument is supported by the fact that since fishers will attempt to maximise revenue, then under constant relative prices, fishers attempt to maximise catch rates.

An understanding of the nature of joint production in the NPF can be enhanced by describing the process of prawn search in the NPF in a way which is consistent with the traditions of search theory discussed in Chapter 2. The literature reviewed in Chapter 2 highlighted advances in search theory as developed in military studies. In this section focus is directed to the technical aspects of search, in particular search tactics, sampling strategies and stopping rules. In the NPF, try nets are used to search for schools of prawn species. In the search for tiger prawns most fishers use try nets alongside their main gear at all times. In banana prawn trawling, the larger nets are used mainly when the search strikes a school. The information from try nets may be useful in arriving at decisions regarding relocating to an alternative ground. In this case the process of searching is clearly distinct from that of harvesting.

In the case of banana prawns, try nets are used occasionally. Search for banana prawns is fairly discrete and involves, in most cases, the search for banana prawn marks[6] whereas the search for tiger prawns is continuous (see Chapter 2 for a descriptions of discrete and continuous search).

Fishers share information on catch rates and catch composition. In addition, fishers experiment with a range of fishing strategies, some of which they hold in common. During the fishing period fishers focus mainly on relocating from one fishing ground to another, as well as maximising their catch. Standard scheduled maintenance of vessels is done during season closure. Routine and daily maintenance and refuelling of vessels is done as sea during the fishing season. Similarly the offloading of prawn product and food reserves for the crew is done at sea from motherships or barges. The bulk of the prawn product is processed and packaged at sea. Fishers have, therefore, the incentive and means to spend as much time fishing.

In both types of searching, the search pattern is determined by the degree of risk-aversion, historical catches, updates from historical catches and fishing information from other fishers. These factors, and the relative revenue of the jointly-produced products will determine, or condition where fishers will search, which fish stock fishers will target, and when fishers will switch to the alternative stock.

The process of search often has management implications. In the case of the NPF seasonal regulation induces a pulse of effort at the opening of the season (Gribble & Dredge 1994, p.1003) which diminishes as closure approaches. The pulse of effort reflects fishers' expectations of increased biomass resulting from closure (Watson, Die & Restrepo 1993) and the competitive nature of fishing.

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[6] Fishers generally define prawn marks as a deep red colouration formed by a dense school of banana prawns. The colouration that appears on the surface of seawater is quite noticeable.

There are two other fisheries that are in the neighbourhood of the Gulf of Carpentaria. These are the Torres Strait Fishery and the Queensland East Coast Fishery. Vessels can fish in all three fisheries, or can be restricted to fishing in selected fisheries. In the case of the former, fishing effort is distributed among these geographically separated fisheries.

The banana prawns of the eastern Gulf of Carpentaria constitute by far the most important commercial prawn in the north of Australia (Clark & Kirkwood 1979, p.1305). These prawns are much more heavily-exploited than are the stocks of alternative species because of their somewhat unusual habit of forming dense schools or boils. The implications for management of commercial fishing patterns in the NPF (and vice versa) are therefore significant.

3.4 Fishers' Search Strategies and Patterns

The following observations help characterise search strategies and patterns in the NPF.

- Fishers in the NPF search using the grid system in general but with the aid of advanced navigation and fish-finding equipment for sampling prawn concentration profiles and identifying schools of fish (Robins & Sachse 1994a, 1994b).
- The type of technology used in fish finding has significant implications for the level of search cost and fishers' optimal searching or stopping rules.
- The experience of the skipper is likely to play a significant part in the search process. Inexperienced skippers are likely to imitate the search behaviour of the more experienced fishers. Over time the learning of search tactics may lead to a diminution of differences in search and harvesting outcomes between skippers.
- In the NPF fishers sample their favourite fishing grounds or areas of high concentration profile three or four times. There is, generally, a limit on the number of search 'bouts' in a concentration profile or within patches that fishers are willing to make. This limit depends on factors such as the desirability of the patch as a fishing ground, the catch history, and weather and general fishing conditions.

- After sampling a number of times fishers quit a patch, or end their patch residence time, and move to the next patch. This kind of behaviour suggests that there are some stopping rule(s) in search behaviour to which fishers respond. In general, patches with the highest prawn concentration are visited first in every statistical fishing zone (SFZ). Other patches are visited on an experimental basis.
- As the prawn fishing season progresses, the level of harvesting within SFZs in the western part of the Gulf increases (Gribble & Dredge 1994). The eastern part of the Gulf is preferred at the start of the prawn season because of the abundance of banana prawns at that time (Robins & Sachse 1994a). Fishing for banana prawns is intense in Weipa at the start of the season and then moves gradually from Weipa to Groote through Mitchell, Karumba, Mornington and Vanderlins, in response to spatial and temporal variability of catch (Gribble & Dredge 1994).
- There is reliable information about fish abundance and fishery regulations in all SFZs available to all fishers. It is reasonable, therefore, to assume that fishers allocate their effort such that the expected marginal revenue from additional search and fishing effort equals the expected addition to costs.

In modelling fishing behaviour in the NPF and introducing the Markov framework, it is important to note the following:

- Fishers exhibit traditional patterns of behaviour and a large portion of the observed mobility is due to these patterns which are influenced by changing catch opportunities (Allen & McGlade 1986; Watson, Die & Restrepo 1993). These patterns of fishing behaviour also result from learning through seasonal searching and harvesting. Harvesting patterns are, therefore, likely to be systematic over time and space.
- Fishers respond to CPUE in different areas. Fishers compare economic returns expected in alternative fishing grounds and are likely to relocate if the expected net benefit from fishing in the current fishing ground is lower than returns realised in alternative fishing grounds.
- The fisher's risk-taking behaviour depends on the likelihood of striking very rich boils of banana prawns in any random search or the likelihood of sampling an area with a high tiger prawn concentration.

- Although the movement of fishers from Weipa to Groote may seem systematic, the movement within SFZs may show large unsystematic variation since fishers still have to make decisions regarding the choice of the precise fishing location within each SFZ. The choice of the fishing location within each SFZ is made in consideration of the estimate of the potential net catch value in all SFZs and fishing grounds.
- Random spatial and temporal search, or unsystematic variation in search, is primarily due to experimental patch-sampling, probing, or the simple acquisition and/or updating of information. The experimental search is done on the basis of either information from other fishers or reflects individual risk-taking behaviour.

3.5 Data

Confidential daily data were provided by the Division of Marine Research of CSIRO. For each vessel the data include the day of the fishing season[7], latitude, longitude and catch of the four species, namely; tiger prawns *(Penaeus esculentus)*, blue-leg king prawns (*Penaeus latisulcatus*), banana prawns *(Penaeus merguiensis)* and endeavour prawns (*Metapenaeus endeavouri*). Data on vessel characteristics include the following records on gear: when the vessel had a Global Positioning Satellite (GPS) system device installed; when the vessel had a plotter installed[8]; headrope length used during the tiger and banana prawn seasons; and, the length of the vessel.

The data span the four fishing periods 1991 through 1994 and are reported on the basis of fishing days, where a fishing day is defined as any day in which at least one vessel reported search, fishing and/or catch. The total record covers over 98 028 daily fishing trips (boat days or trip days). As shown in Table 3.1 the number of boats participating in the fishery over the period 1991 to 1994 ranged from 127 in 1993 to 172 in 1991.

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[7] The term fishing season is reserved for periods during which either tiger or banana prawns were targeted mainly. The term fishing period will be reserved for the year of fishing.

[8] Additional uses in fishing include the storage of data on catches, and size and position of banana prawn marks in the NPF.

Catch and effort estimates were derived from a combination of logbook information and landing figures. The catch is the mass, in kilograms, of prawns caught by a vessel. Effort is recorded as boat days, that is the number of days a vessel is out at sea, or the number of boat days or trip days to a selected or targeted fishery[9]. Catch and effort data were partitioned into the tiger and banana prawn fisheries according to the composition of catch in logbook records[10]. If 50 percent or more of daily catch was banana prawns, the boat was classified as fishing for banana prawns, otherwise it was classified as being in the tiger prawn fishery for that day.

The 50 percent rule as used in the data set provided to the researcher is an assumption that has been used to represent targeting behaviour in the NPF. To the knowledge of the researcher, no formal study has been done on targeting behaviour of NPF fishers. The assumption made so far has been that if 50 percent of the catch comprises banana prawns then the fisher must have been targeting banana prawns.

Admittedly, this is an "after-the-effect" classification of targeting behaviour. A more effective classification would have been to establish prior to the start of the fishing trip what the target species were[11]. It is important to point out that for most fishing grounds in the NPF the 50 percent rule may not necessarily yield results any different from those obtained using other classification, especially during the early weeks of the banana prawn or tiger prawn fishery.

The main reason for the likely lack of any significant difference is that the respective recruitment patterns of the banana and tiger prawn species are different (Somers & Kirkwood 1984; Somers 1994) and their habitats are also different (Somers 1994b). The migration and schooling behaviour of the prawn species are also different (Hall & Watson 2000; Kenyon, Die & Loneragan 2000).

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[9] Note that boat days represent nominal fishing effort.

[10] A crude measure of catch per unit effort (CPUE) for the fleet can be derived as the catch per day for the entire fleet. The crude CPUE per vessel in a fishery is, therefore, the catch during the season in a fishery divided by the number of boat days.

[11] This would require a process of interviewing fishers, modifying the logbook and/or using observer data. In my opinion a cost-effective way is to modify the logbook to reflect the targeting behaviour.

The banana prawn season is shorter than the tiger prawn fishing season. In this regard most, if not all fishers target banana prawns in the first 4 to 6 weeks, and then switch to tiger prawns. Somers (1994b, p.57) indicated that "within a week the fleet will have between 50 and 80 percent of the annual Gulf of Carpentaria banana prawn catch". When most fishers switch to tiger prawns, other fishers may opt to target banana prawns. Because of the differences in the spatial distribution of banana and tiger prawns, the fleet targeting banana prawns will relocate to those spatial units (fishing grounds) that are banana prawn fishing grounds. For such fishers tiger prawn will be the marketable by-catch (the incidental catch).

Similarly, those fishers targeting tiger prawns will select fishing grounds that are predominantly tiger prawn fishing grounds, and banana prawns will become the incidental catch. It is reasonable, therefore, to argue that if a fisher targets a banana prawn fishing ground, then the bulk of their catch (over 50 percent) will generally consist of banana prawns. Similarly, a fisher targeting a tiger prawn fishing ground will generally have the bulk of their catch comprising tiger prawns. In this respect, targeting behaviour of fishers in the NPF can be represented by fisher's ground choice. Fishers' ground choice can be used, in this case, as a proxy of fishers' species targeting behaviour[12]. This proxy also suits the Markov modelling of fleet dynamics quite well, since the transition probabilities also reflect, therefore, changes in the fishers' expectation of catch.

The data show a logbook record of catch and effort activities of each vessel that had the right to fish between Koolan Island in Western Australia and Cape York in Queensland. The data cover the area between longitude 121°S and 142°E, and latitude 10°S and 17°S. This area bounds the Kimberley Prawn Fishery (KPF) and the Northern Prawn Fishery (NPF) and is referred to throughout the thesis as the Management Zone (MZ)[13].

[12] A formal study on targeting behaviour is needed to test this 50% rule.

[13] The NPF is defined as the sea area bounded in 127°E to 142°E and 10°S to 18°S. The KPF is bounded between 121°E to 127°E and 10°S to 17°S.

Even though the two fisheries are now administered by different governments, the fisheries are closely aligned. The KPF is under the control of the Western Australian government and the NPF is managed by the Australian Commonwealth government. However, nearly all the NPF fleet has access rights to the KPF and many of the regulations of these two fisheries are related (Sachse & Robins 1994). Fishers' ground choices in the NPF are influenced by catch opportunities and fleet movements in the KPF, and vice versa. Fleet movements and catch opportunities in the KPF are, therefore, important in understanding fleet dynamics in the NPF, and it is appropriate to include the KPF in a model of fleet movements in the NPF[14].

Data on latitude and longitude were recoded to identify the statistical fishing zones (SFZs) and statistical fishing grounds (SFGs) in which search and fishing were conducted. The MZ is divided into 18 SFZs (see Figure 3.1). The SFZs are coded from 41 through 62, and are referred to as the two-digit fishing grounds. Each of the SFZs shown in Figure 3.2 are subdivided into at least two statistical fishing grounds, making a total of 73 SFGs.

The SFGs are coded from 411 through 626, and are referred to as the three-digit fishing grounds. Some constituent parts of the MZ (namely: Albatross Bay (AB)[15], the Gulf of Carpentaria (GoC)[16], Joseph Bonaparte Gulf (JBG)[17], the NPF[18] and the KPF[19] are examined individually in this chapter. Fishing patterns of vessels participating in the NPF include, therefore, harvesting and search activity in the GoC, JBG and AB, among other fishing grounds.

[14] The KPF will be included in simulating the effects of ground closure on NPF fleet dynamics as reported in Chapter 6 of this thesis.

[15] All fishing grounds coded at 422 constitute AB.

[16] All fishing grounds coded less than or equal to 481 constitute the GoC.

[17] The set of grounds coded 534 through 540 constitute the JBG.

[18] All fishing grounds coded at or less than 540 constitute the NPF.

[19] All fishing grounds coded above 540 comprise the KPF.

Figure 3.1 Two-Digit SFZs in the MZ

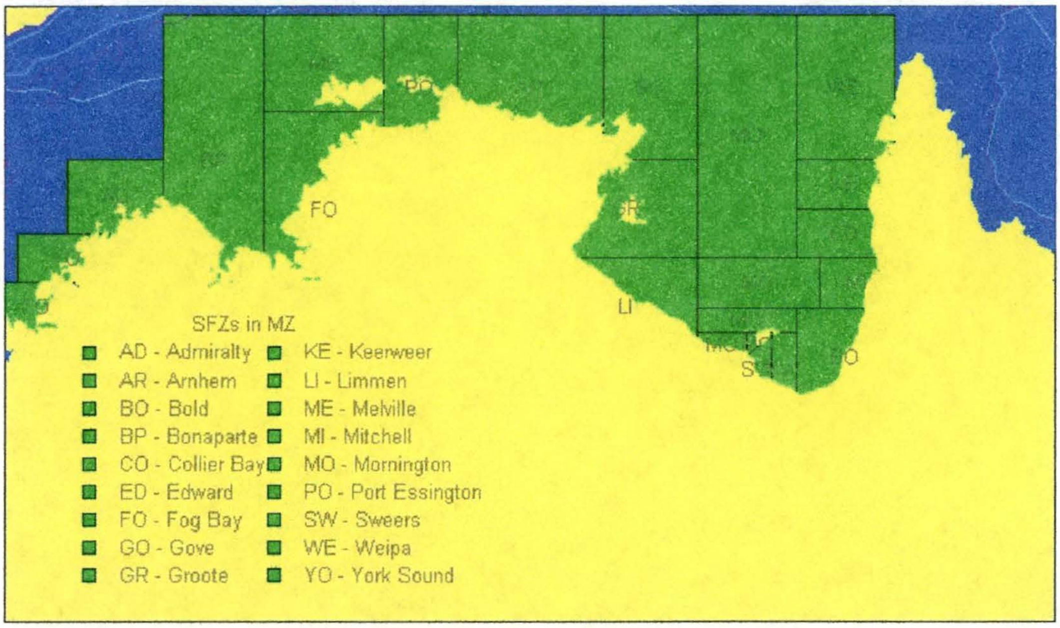
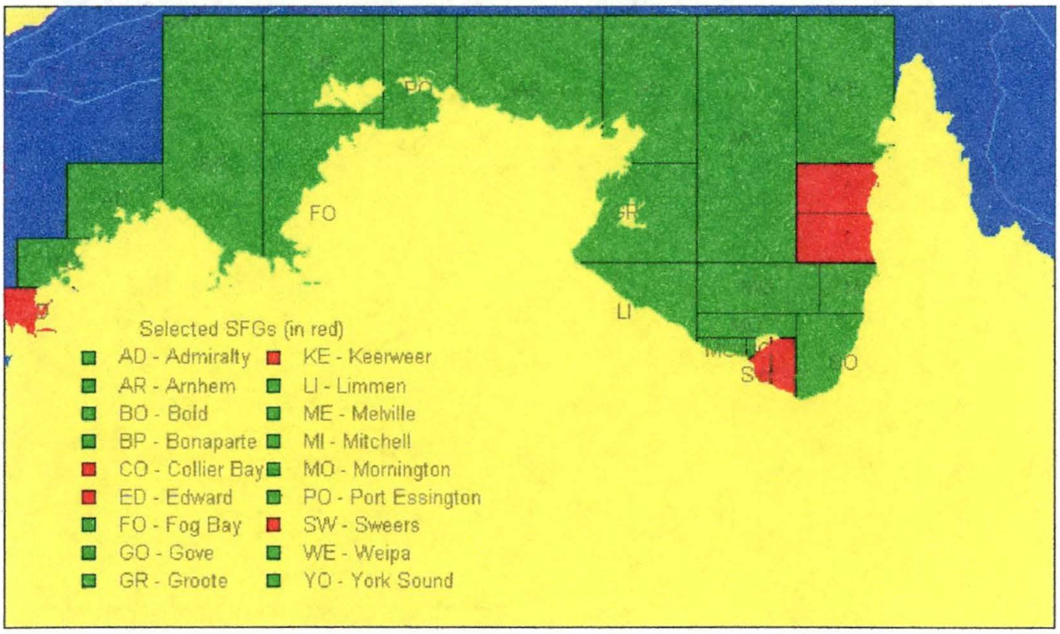


Figure 3.2 Selected (three-digit) SFGs in the MZ



The entire data set has been organised in order to report the variables described in Table 3.2. It is clear from the chronology of the development of the NPF outlined in Section 3.2 that the variables related to catch, effort, boat characteristics, and gear characteristics have been important in shaping management policy in the NPF. The management policy of the NPF has focussed on input controls, and area and seasonal closures[20]. Data on closures for the periods 1991 through 1994 were obtained from fishery production statistics (Sachse 1991, 1992; Sachse & Robins 1993, 1994; Pownall 1994). The data are shown in Table 3.3. Detailed changes in the structure of the fishery in terms of gear restriction and vessel numbers were also compiled. It is noteworthy that 1993 is the first season after the implementation of the compulsory reduction phase of the industry restructuring program that led to the removal of 43 boats from the fishery (Sachse & Robins 1994).

Table 3.2 Variables and Definitions

VARIABLE NAME	DEFINITION (and units of measurement)
CODE	Numeric name of the vessel
FDATE	Actual date of fishing
FDAY	Day of fishing in a season
LATI	Latitude reported
LONG	Longitude reported
BAN	Catch of banana prawns (in kilograms)
TIGER	Catch of tiger prawns (in kilograms)
KING	Catch of king prawns (in kilograms)
ENDEV	Catch of endeavour prawns (in kilograms)
MIXED	Catch of mixed species (in kilograms)
FISH	Classification of catch according to species targeted
GROUND	Recoded values or one-dimensional translation of longitude and latitude data
BGEAR	Headrope length during banana prawn trawling(cm)[21]
TGEAR	Headrope length during tiger prawn trawling (cm)
LENGTH	Length of vessel (in metres)
GPSYEAR	Year in which GPS was installed on vessel
PLOTYEAR	Year in which plotter was installed on vessel
FISHERY	Coded values for GoC, JBG, AB, NPF and KPF
SKIPPER	Skipper's experience with GPS (in years)

[20] The main policies analysed in Chapter 6 of this thesis are, therefore, area closures and season shortening.

[21] Total headrope length is calculated as the product of the number of nets and the average length of each net.

3.6 Descriptive Analysis of Fishing Patterns

3.6.1 Summary Statistics on Seasons, Catch and Effort

A summary of fishing seasons and fishing activity in the MZ for the years 1991-1994 is presented in Table 3.3. The dates provided in Table 3.3 and referred to in other tables are based on the official dates for the opening and closure of the NPF fishing season. The opening date of the fishing season has been based on an assessment of the biology of the banana prawn stocks in conjunction with prices received in the export markets (Somers 1994b, p.57).

The total banana prawn catch in 1992 and 1994 was lower than total tiger prawn catch in each of these years while banana prawn catch exceeded tiger prawn catch in years 1991 and 1993. Both total and mean landings of banana prawns[22] were lower in years 1992 and 1994, than in the years 1991 and 1993[23]. The mean banana prawn catch was lowest in 1992. The numbers in parenthesis are the standard deviations of banana prawn and tiger prawn catch. Banana prawn catch was quite variable with a mean raw landing of 3 841 163 kgs and a standard deviation of 1 835 610 reported for the period. Tiger prawn landings were fairly stable with a mean of 3 075 791 kgs and a standard deviation of 37 647 reported for the period. The length of the season over the period 1991-1994 did not vary considerably. However the number of fishing grounds visited annually by fishers fell from 60 to 49 over the period 1991 through 1994.

Tables 3.4 through 3.9 presents these variables for the entire MZ and component fishing grounds of the MZ. In presenting the results displayed in Table 3.4 through Table 3.9, the descriptive statistics are coded as follows.

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[22] The mean prawn catch is calculated as the total catch of the selected species divided by the total number of boat days.

[23] The mean prawn catch per boat can be obtained from dividing mean prawn catch by the number of vessels that participated in the fishery over the selected fishing period.

Code		Code	
1	Number of Fishing Days	2	Number of Grounds Fished
3	Total Banana Prawn Catch (kgs)	4	Mean Banana Prawn Catch (kgs/day)
5	Total Tiger Prawn Catch (kgs)	6	Mean Prawn Tiger Prawn Catch (kgs/day)
7	Number of Boats	8	Number of Trip Days
9	Standard Deviation of Banana Prawn Catches (kgs/day)	10	Standard Deviation of Tiger Prawn Catches (kgs/day)

Table 3.4 reports for the entire MZ. The ratios of trip days for tigers prawns and trip days for banana prawns to total trip days for the years 1991 through 1994 are calculated, indicating that 73.7%, 80.4%, 72.3% and 87.7% of total boat days were spent in tiger prawn fishing. The data reported in Table 3.4 suggest that for the MZ, (i) the number of fishing grounds in the tiger prawn fishery is lower than in the banana prawn fishery in all periods 1991 through 1994; (ii) the number of fishing grounds sampled in each period between 1991 and 1994 declined (that is, fishers are tending to search in fewer grounds for both species).

In addition, the number of trip days during the tiger prawn season is higher than during the banana prawn season for the years 1991 through 1994. Adjusting for the differences in the length of the fishing seasons, there is clearly heavier fishing effort for tiger prawn production. A further adjustment can be made for fleet size. This can be calculated as the number of boats or the number of boats actually licensed to fish during the season. The result presented in Tables 3.5 through 3.9 suggest a consistent preference in the allocation of nominal fishing effort to the searching for and harvesting of tiger prawns. Results reported in Table 3.5 suggest that in Albatross Bay (AB), the total number of fishing days for both species is quite variable, although more effort is still allocated to tiger prawn fishing. Unlike other components of the MZ, however, the proportion of vessels targeting banana prawns in the AB is higher than that targeting tiger prawns.

Table 3.3 Catch, Effort and Seasonal Closure During Fishing Periods 1991 through 1994[24]

Year	Banana Prawn Season		Tiger Prawn Season		Total Days Fished	Grounds Selected and Catch Rates		
	Open	Closed	Open	Closed		Grounds (number)	Banana Prawns	Tiger Prawns
1991	1 Apr 8 Jun	9 Jun 31 Jul	1 Aug 1 Dec	2 Dec 31 Mar	227	60	6 715 211 [263.18] (841.80)	3 590 528 [140.72] (132.37)
1992	1Apr 8 Jun	9 Jun 31 Jul	1 Aug 1 Dec	2 Dec 31 Mar	224	59	2 332 051 [87.00] (397.31)	3 038 123 [113.44] (79.83)
1993	1 Apr 21 Jun	22 Jun 31Jul	1 Aug 2 Dec	2 Dec 12 Mar	206	50	4 160 882 [186.33] (651.60)	2 531 791 [113.38] (95.71)
1994	13 Mar 7 Jun	8 Jun 31 Jul	1 Aug 1 Dec	2 Dec 31 Mar	222	49	2 156 506 [92.16] (337.26)	3 142 722 [113.38] (96.99)

Source: Pownall (1994) and CSIRO (1991, 1992, 1993, 1994), data set.

Notes: The numbers in square brackets [ ] are the mean prawn catch (kg/boat day). The numbers in parentheses () are the standard deviations of prawn catch (kg/day).

[24] Note that the dates provided are official dates for opening and closure of the NPF fishing seasons.

Table 3.4 Summary Statistics for the Management Zone (MZ)

	1991			1992			1993			1994		
	FS	**BPS**	**TPS**	**FS**	**BPS**	**TPS**	**FS**	**BPS**	**TPS**	**FS**	**BPS**	**TPS**
1	227	209	208	224	205	214	206	203	199	222	197	221
2	60	55	51	59	54	48	50	48	39	49	46	39
3	6715211	6642548	72663	2332051	2300814	31237	4160882	4131354	29528	2156506	2120366	36140
4	263.18	991.13	6.86	87.08	438.08	1.458	186.33	666.83	1.83	92.16	425.69	1.96
5	3590528	57889	3532639	3038123	35691	3002432	2531791	31564	2500227	3142722	50913	3e+06
6	140.72	8.64	187.77	113.44	6.80	139.45	113.38	5.11	154.77	134.31	10.22	167.87
7	172	169	172	170	167	169	127	125	127	127	126	126
8	25516	6702	18814	26782	5252	21530	22331	6177	16154	23399	4981	18418
9	841.80	1406.43	20.32	397.31	806.94	11.37	651.60	1101.17	14.45	337.26	626.24	14.82
10	132.37	32.45	122.32	79.83	24.33	65.81	95.71	24.95	78.92	96.99	45.02	78.18

Note: The variables shown in code form in column 1 above are the number of fishing days (1), the number of fishing grounds (2), total banana prawn catch (3), mean daily banana prawn catch (4), total tiger prawn catch (5), mean daily tiger prawn catch (6), number of boats (7), number of trip days (8), standard deviation of daily banana prawn catch (9) and standard deviation of daily tiger catch prawn catch (10). The codes 1 through 10 apply to Tables 3.4 through 3.9.

Table 3.5 Summary Statistics for the Albatross Bay (AB)

	1991			1992			1993			1994		
	FS	**BPS**	**TPS**	**FS**	**BPS**	**TPS**	**FS**	**BPS**	**TPS**	**FS**	**BPS**	**TPS**
1	130	36	95	151	36	131	22	110	119	189	51	155
2	1	1	1	1	1	1	1	1	1	1	1	1
3	657597	657369	228	160980	159472	420766	420751	15	1508	179630	175453	4177
4	875.36	1422.88	0.75	154.34	345.93	633.68	1252.24	0.05	2.59	132.28	434.29	4.38
5	29382	88	29294	53417	410	32731	167	32564	53007	163953	25568	138385
6	38.31	0.19	96.05	51.21	0.89	49.29	0.50	99.28	91.08	120.73	63.29	145.06
7	115	111	29	144	135	104	96	30	38	93	84	45
8	767	462	305	1043	461	664	336	328	582	1358	404	954
9	1290.88	1400.79	3.67	346.7	453.96	1278.76	1567.47	0.59	8.3	371.51	576.13	30.33
10	55.06	1.54	45.67	58.88	4.48	63.54	2.77	56.81	51.02	98.52	120.27	76.25

Table 3.6 Summary Statistics for the Gulf of Carpenteria (GoC)

	1991			1992			1993			1994		
	FS	**BPS**	**TPS**	**FS**	**BPS**	**TPS**	**FS**	**BPS**	**TPS**	**FS**	**BPS**	**TPS**
1	191	115	180	191	101	189	206	110	199	209	97	208
2	30	28	25	30	26	25	27	25	22	28	25	25
3	4998423	4965914	32509	1347337	1335224	12113	2134597	2113955	20642	928955	899857	29098
4	273.09	1365.39	2.22	69.79	610.81	0.71	133.94	845.24	1.54	53.70	40154	1.93
5	2939738	28714	2911024	2429459	8511	2420948	2104151	21912	2082239	26030963	41447	2589516
6	160.02	7.89	198.48	125.85	3.89	141.42	132.03	8.76	154.97	152.09	18.49	171.97
7	165	159	162	162	152	160	124	120	121	124	116	123
8	18303	3637	14666	19305	2186	17119	15937	2501	13436	17299	2241	15058
9	928.28	1687.17	15.35	412	1081.03	6.40	620.38	1360.72	12.31	281.98	687.93	15.11
10	138.51	35.76	128.10	74.05	22.25	63.08	90.08	35.33	77.7	92.50	63.83	78.57

Note: The variables shown in code form in column 1 above are the number of fishing days (1), the number of fishing grounds (2), total banana prawn catch (3), mean daily banana prawn catch (4), total tiger prawn catch (5), mean daily tiger prawn catch (6), number of boats (7), number of trip days (8), standard deviation of daily banana prawn catch (9) and standard deviation of daily tiger catch prawn catch (10). The codes 1 through 10 apply to Tables 3.4 through 3.9.

Table 3.7: Summary Statistics for the Northern Prawn Fishery (NPF)

	1991			1992			1993			1994		
	FS	**BPS**	**TPS**	**FS**	**BPS**	**TPS**	**FS**	**BPS**	**TPS**	**FS**	**BPS**	**TPS**
1	227	201	207	219	202	209	206	203	199	222	193	221
2	54	49	45	53	48	42	44	42	35	44	41	37
3	6355921	6291299	64622	2170177	2141878	28299	4108565	4080935	27630	2107247	2071135	36112
4	256.92	1004.52	3.50	82.42	433.32	1.32	185.43	676.21	1.71	90.61	427.48	1.96
5	3553237	55064	3498173	3025349	33106	2992243	2529860	30937	2498923	3141374	50779	309059 5
6	143.63	8.79	189.34	114.89	6.70	139.90	114.18	5.13	155	135.08	10.48	167.88
7	172	169	172	170	167	169	127	125	126	127	126	126
8	24739	6263	18476	26332	4943	21389	22157	6035	16122	23255	4845	18410
9	841.02	1429.86	18.89	386.54	802.45	10.14	652.69	110.2	12.92	355.58	629.55	14.82
10	132.75	32.98	122.37	79.51	24.66	65.66	95.62	25.14	78.80	96.54	45.62	77.87

Table 3.8: Summary Statistics for the Kimberley Prawn Fishery (KPF)

	1991			1992			1993			1994		
	FS	BPS	TPS	FS	BPS	TPS	FS	BPS	TPS	FS	BPS	TPS
1	149	106	96	110	86	53	62	52	21	54	48	8
2	6	6	6	6	6	6	6	6	4	5	5	2
3	359290	351249	8041	161874	158936	2938	52317	50419	1898	49259	49231	28
4	462.41	800.11	23.79	359.72	514.36	20.84	300.67	355.06	59.31	342.08	361.99	3.50
5	37291	2825	34466	12774	2585	10189	1931	627	1304	1348	134	1214
6	47.99	6.44	101.97	28.39	8.37	72.26	11.10	4.42	40.75	9.36	0.99	151.75
7	44	42	28	38	33	32	26.00	25	11	21	20	4
8	777	439	338	450	309	141	174.00	142	32	144	136	8
9	842.29	995.59	55.42	758.91	872.2	61.21	841.09	513.28	134.23	483.25	490.02	6
10	74.12	23.61	82.15	44.53	18.14	52.95	29.10	14.86	50.48	88.66	3.74	346.09

Note: The variables shown in code form in column 1 above are the number of fishing days (1), the number of fishing grounds (2), total banana prawn catch (3), mean daily banana prawn catch (4), total tiger prawn catch (5), mean daily tiger prawn catch (6), number of boats (7), number of trip days (8), standard deviation of daily banana prawn catch (9) and standard deviation of daily tiger catch prawn catch (10). The codes 1 through 10 apply to Tables 3.4 through 3.9.

Table 3.9: Summary Statistics for the Joseph Bonaparte Gulf (JBG)

	1991			1992			1993			1994		
	FS	BPS	TPS	FS	BPS	TPS	FS	BPS	TPS	FS	BPS	TPS
1	155	144	46	170	154	41	161	159	9	166	151	25
2	5	5	4	5	5	3	4	4	4	4	4	4
3	445405	442618	2787	199438	198118	1320	774271	774237	34	590329	589502	827
4	401.99	438.67	28.15	250.24	271.39	19.70	589.25	593.74	3.4	511.99	524	29.54
5	13334	4901	8433	7813	1886	5927	1997	645	1352	3708	1255	2453
6	12.03	4.86	85.18	9.80	2.58	88.46	1.52	0.49	135.20	3.22	1.12	87.61
7	67	67	22	55	55	22	52	52	7	46	46	9
8	1108	1009	99	797	730	67	1314	1304	10	1153	1125	28
9	506.18	515.87	42.71	378.45	388.45	40.54	631.36	631.68	5.39	455.14	454.21	48.64
10	36.03	14.01	81.55	33.63	9.83	75.15	28.43	2.82	295.28	18.87	5.54	78.29

3.6.2 Summary Statistics on Fishing Technology

Mean headrope lengths used during the banana and tiger prawn seasons, for the period 1988 through 1992, and descriptive statistics on the installations of GPS in the MZ are reported in Table 3.10. The mean catches of banana and tiger prawns are also reported. Determining what has happened to the mean headrope length over time is integral to an understanding of commercial search patterns. It is generally agreed that headrope length is related to wing-spread and swept area. Therefore, setting the headrope length controls the effectiveness of fishing gear. Headrope length adjustments represent, therefore, a form of input control, and have been used extensively in the management of the NPF (see Section 3.2).

The acquisition of GPS may affect searching patterns and improve output. In addition, further increases in output following the installation of GPS equipment may occur as a result of the 'learning-by-doing' effect. The differences in skippers' experience with GPS may account for differences in mean catch. It is, therefore, of interest to establish the effect of GPS on the catch of vessels that have similar search patterns (that is, identical ground choice and/or ground choice configurations).

Available information suggests that individual vessels in the NPF were 'skippered' by the same person throughout the period of analysis[25]. A skipper's GPS experience can, therefore, be related to the number of years a vessel has had GPS installed. It is reasonable to assume that all skippers use GPS if the vessel has GPS installed. The data shown in Table 3.10 reveals the following: (i) only 7.6 percent of the vessels had GPS installed in 1988; (ii) a further 66.2% of vessels installed GPS in 1989, 1990 or 1991; (iii) by 1992 77.6% of the fleet had GPS installed.

[25] This is based on personal communication with Carol Robins and Brian Taylor. Confidential records of skipper names and boat names are held by CSIRO.

Using data for 1991 through 1994, the results in Tables 3.11 and Table 3.12 below suggest that mean banana prawn catch is generally higher for vessels that have longer periods of GPS and plotter use[26]. This suggests increased fishing power due to the increased technical and economic efficiency of searching that is a likely result of the use of GPS and plotters. The results shown in Table 3.11 and Table 3.12 highlight these findings. The analysis presented in this section is fairly simple. A simple analysis of differences in catch rates of vessels that had GPS installed does not incorporate other variables that may be quite important such as tow duration and effective fishing effort. The reader is referred to a summary of advanced research methods on evaluating the effects of GPS on fishing power by Robins, Wang and Die (1996, 1998), in Section 3.7 of the thesis.

[26] Plotter availability can confer a huge advantage in that records of past events can be recorded easily. It is generally believed that GPS and plotters have increased fishing power (see Section 3.7).

Table 3.10 Proportion of Vessel GPS and Plotter Installations

Year	*Installing GPS (%)*	*Installing Plotters (%)*	*Mean Headrope Length (cm)*	*Mean Banana Prawn Catch (kg/day)*	*MeanTiger Prawn Catch (kg/day)*
1988	7.6	6.8	2265.26	288.79	134.40
1989	21.5	12.2	2172.96	308.02	140.09
1990	19.0	14.8	2139.87	247.82	147.31
1991	25.7	30.8	2173.89	234.42	140.21
1992	3.8	9.7	2065.35	224.78	130.92

TABLE 3.11 GPS and Plotter Acquisition, Catch and Number of Vessels in 1991-1994

	1991			*1992*			*1993*			*1994*		
	Number of Vessels	Mean Banana Prawn Catch (kg/day)	Mean Tiger Prawn Catch (kg/day)	Number Of Vessels	Mean Banana Prawn Catch (kg/day)	Mean Tiger Prawn Catch (kg/day)	Number of Vessels	Mean Banana Prawn Catch (kg/day)	Mean Tiger Prawn Catch (kg/day)	Number of Vessels	Mean Banana Prawn Catch (kg/day)	Mean Tiger Prawn Catch (kg/day)
A	172	263	141	170	87	113	127	186.3	113	127	92.16	134.31
B	171	264	141	169	87	114	127	186.33	113.88	122	91.93	134.90
C	4	211	170	3	135	116	1	228.82	106.42	1	48.59	140.11
D	1	146	63	1	83	25	0	0		5	99.89	114.64

Key:

A: Number fishing in selected year

B: Number with GPS only, or GPS and Plotter and fishing in selected fishing period.

C: Number with GPS only, and fishing in selected fishing period

D: Number without GPS at all

TABLE 3.12 Skippers' GPS and Plotter Experience, Catch and Number of Vessels in 1991-1994

	1991			*1992*			*1993*			*1994*		
	Number of Vessels	Mean Banana Prawn Catch (kg/day)	Mean Tiger Prawn Catch (kg/day)	Number of Vessels	Mean Banana Prawn Catch (kg/day)	Mean Tiger Prawn Catch (kg/day)	Number of Vessels	Mean Banana Prawn Catch (kg/day)	Mean Tiger Prawn Catch (kg/day)	Number of Vessels	Mean Banana Prawn Catch (kg/day)	Mean Tiger Prawn Catch (kg/day)
0	1	145.76	62.71	1	83.17	24.74	-	-	-	5	99.89	114.64
1	61	234.42	140.21	9	73.15	105.55	-	-	-	5	107.80	117.86
2	41	247.82	147.31	56	76.46	108.62	4	263.92	115.16	39	73.85	134.80
3	49	308.20	140.09	41	79.38	118.13	46	158.92	107.76	29	94.42	133.41
4	15	288.79	134.40	46	106.76	117.51	29	186.09	114.36	36	99.50	137.45
5	-	-	-	17	93.22	116.14	36	198.56	119.14	13	117.54	136.45
6	-	-	-	-	-	-	12	236.25	114.27	-	-	-

Key:

0 No GPS Experience at all

1 GPS been installed for 1 year

2 GPS has been installed for 2 years

3 GPS has been installed for 3 years

4 GPS has been installed for 4 years

5 GPS has been installed for 5 years

6 GPS has been installed for 6 years

3.6.3 Summary Statistics on Fleet Participation

Fleet participation is defined, in this thesis, as the total number of boats participating in a fishery on any selected day[27]. The fleet participation rate measures the proportion of licensed vessels participating in a fishery on a particular day[28]. The participation levels of vessels searching for banana and/or tiger prawn species in the MZ, in the fishing periods 1991 through 1994, are shown graphically in Figures 3.3 to 3.10[29]. The series "ban" refers to the vessels targeting banana prawns. The series "tig" refers to those vessels targeting tiger prawns. The composite series "b+t" refers to those vessels targetting either prawn species or both prawn species.

The results can be compared directly across the fishing periods 1991 and 1992 since these periods have the same opening and closure dates. Seasons 1993 and 1994 cannot be compared directly to the other fishing periods because of differences in season length and timing of closures. However, all four fishing periods can be compared on the basis of the day of the fishing season, instead of the calendar day of fishing, under the assumption that once the season is open, fishing activity does not depend, substantially, on the date of opening.

The general trend is one of an increasing number of vessels harvesting tiger prawns and a decreasing number of vessels pursuing banana prawns. At the start of the season most of the skippers are pursuing banana prawns. The preference for tiger prawns during the tiger prawn season is quite clear and well pronounced. There is, however, still a considerable amount of activity targeted at banana prawns but this activity declines to very low levels of fleet participation. Of particular interest is the time during which equal proportions of vessels pursue either banana prawns or tiger prawns. The term 'reflected indifference' refers to the point at which equal proportions of fishers target each species.

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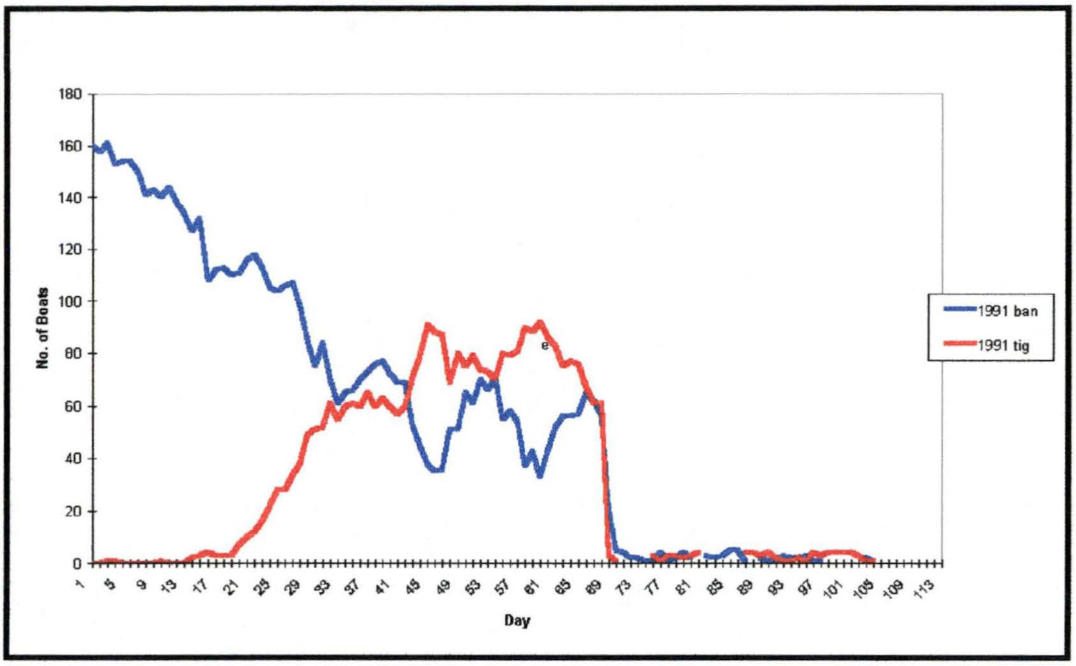
[27] For example, if 20 boats fish on day 1, the level of participation is 20.
[28] For example, if 20 out of 100 licensed vessels fish on day 1, the participation rate is 20 percent.
[29] These results refer to participation in the MZ.

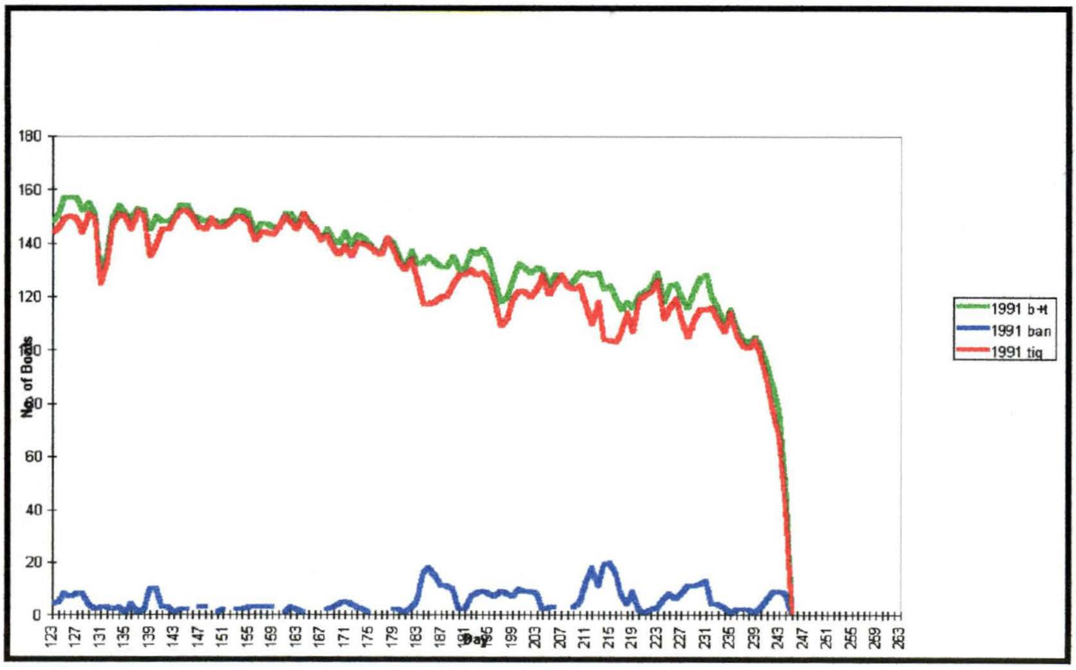
Figure 3.3 Fleet Participation in 1991 Banana Prawn Fishery



Note:

The series "1991 ban" refers to the number of vessels targeting banana prawns in 1991
The series "1991 tig" refers to the number of vessels targeting tiger prawns in 1991

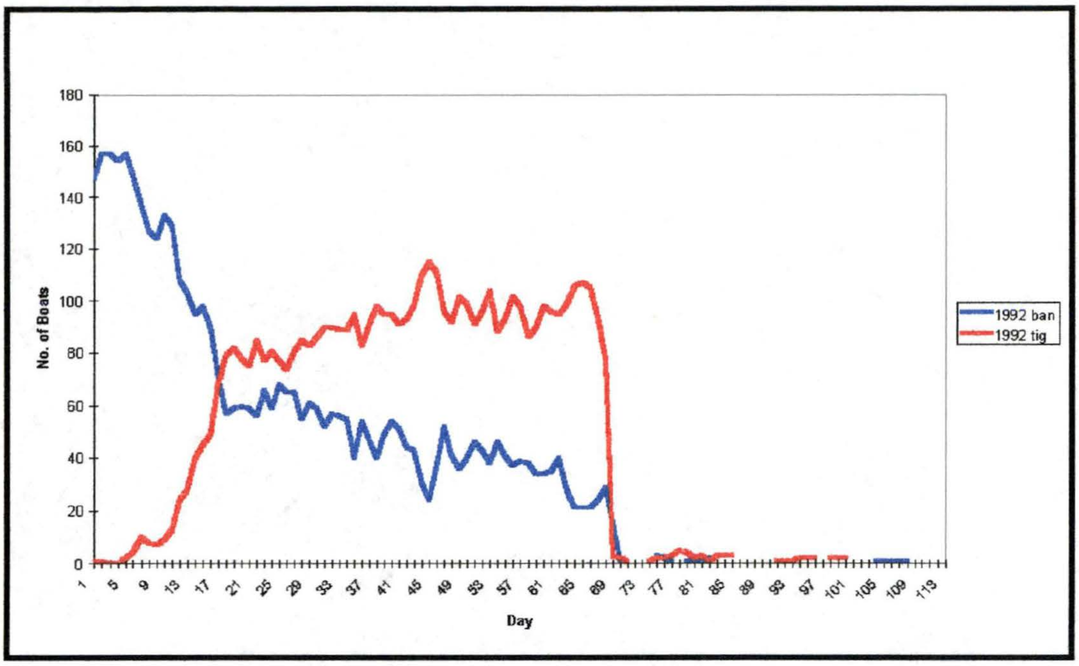
Figure 3.4 Fleet Participation in 1991 Tiger Prawn Fishery



Note:

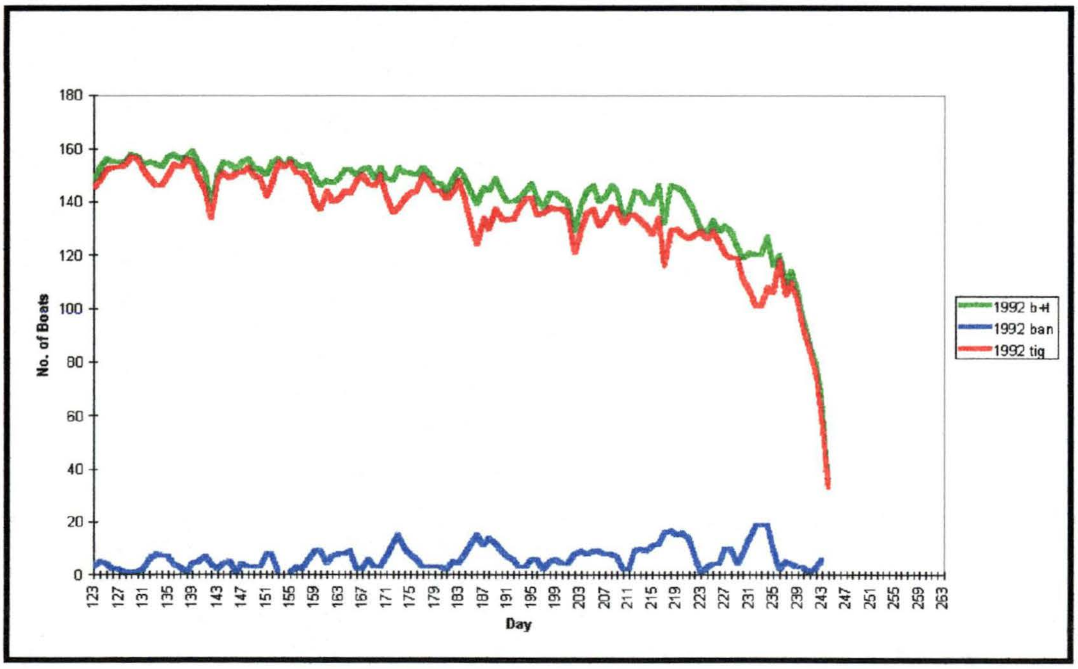
The series "1991 ban" refers to the number of vessels targeting banana prawns in 1991
The series "1991 tig" refers to the number of vessels targeting tiger prawns in 1991.
The series "1991 b +t" refers to the number of vessels targeting banana and tiger prawns in 1991.

Figure 3.5 Fleet Participation in 1992 Banana Prawn Fishery



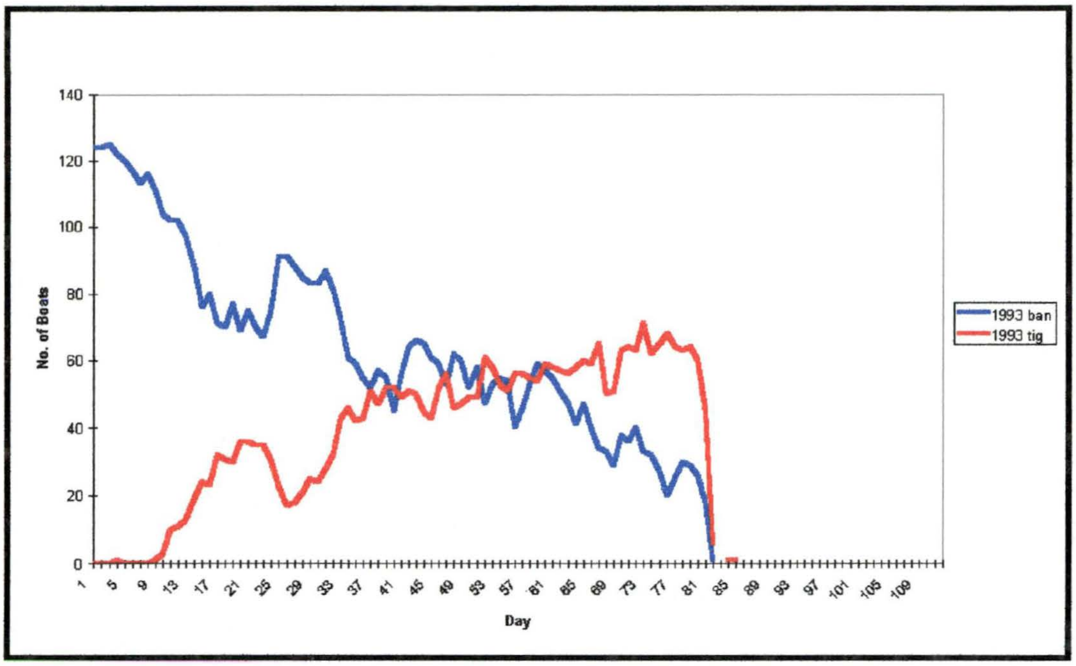
Note:
The series "1992 ban" refers to the number of vessels targeting banana prawns in 1992.
The series "1992 tig" refers to the number of vessels targeting tiger prawns in 1992.

Figure 3.6 Fleet Participation in 1992 Tiger Prawn Fishery



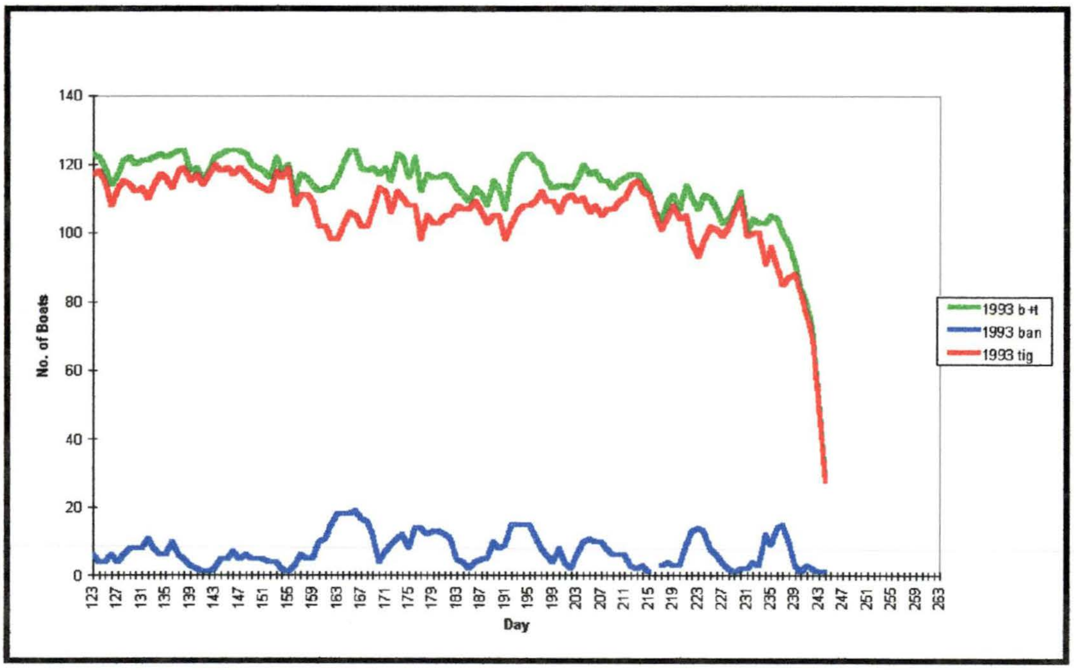
Note:
The series "1992 ban" refers to the number of vessels targeting banana prawns in 1992
The series "1992 tig" refers to the number of vessels targeting tiger prawns in 1992.
The series "1992 b +t" refers to the number of vessels targeting banana and tiger prawns in 1992.

Figure 3.7 Fleet Participation in 1993 Banana Prawn Fishery



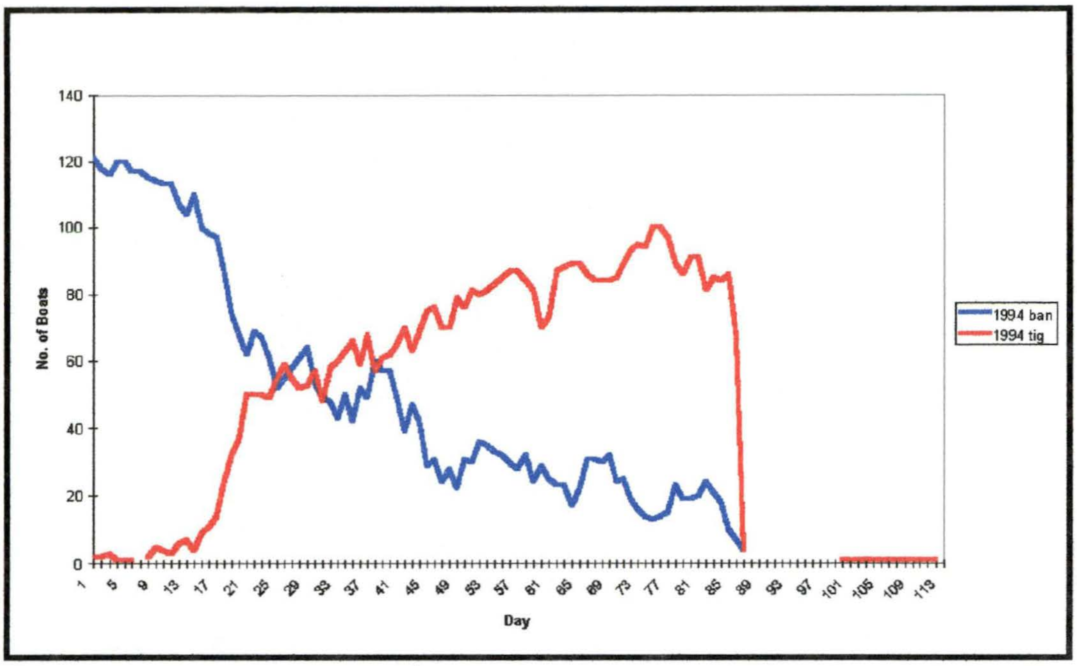
Note:
The series "1993 ban" refers to the number of vessels targeting banana prawns in 1993.
The series "1993 tig" refers to the number of vessels targeting tiger prawns in 1993.

Figure 3.8 Fleet Participation in 1993 Tiger Prawn Fishery



Note:
The series "1993 ban" refers to the number of vessels targeting banana prawns in 1993
The series "1993 tig" refers to the number of vessels targeting tiger prawns in 1993.
The series "1993 b +t" refers to the number of vessels targeting banana and tiger prawns in 1993.

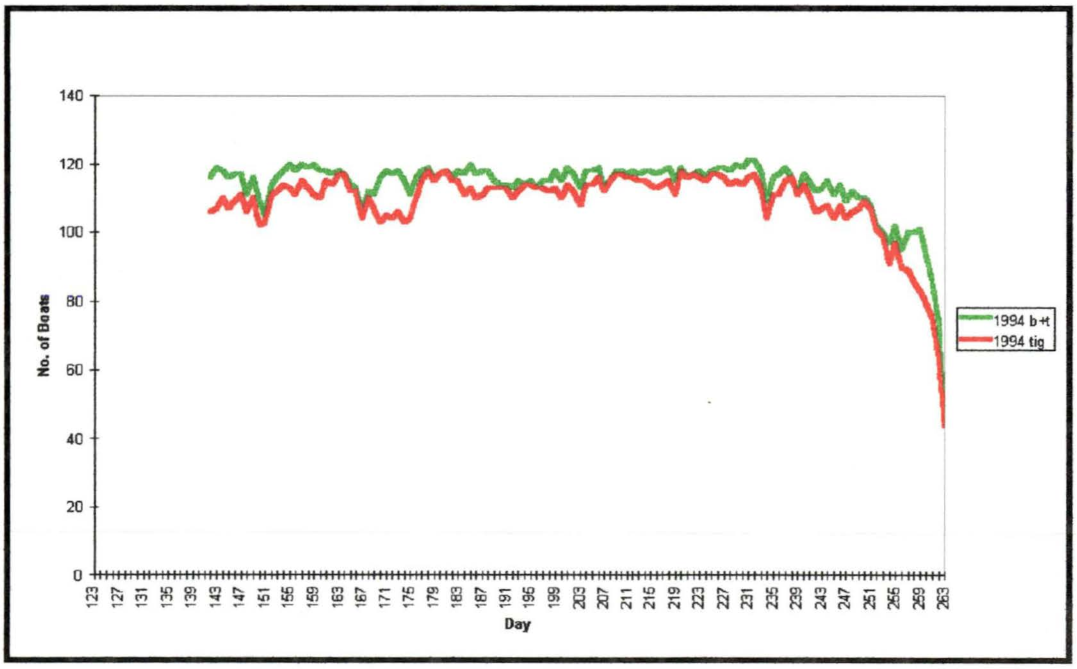
Figure 3.9 Fleet Participation in 1994 Banana Prawn Fishery



Note:

The series "1994 ban" refers to the number of vessels targeting banana prawns in 1994
The series "1994 tig" refers to the number of vessels targeting tiger prawns in 1994.

Figure 3.10 Fleet Participation in 1994 Tiger Prawn Fishery



Note:

The series "1994 tig" refers to the number of vessels targeting tiger prawns in 1994.
The series "1994 b +t" refers to the number of vessels targeting banana and tiger prawns in 1994.

This point of reflected indifference occurs at day 29 and continues through day 69 in 1991; and at day 13 and continues through 18 in 1992. The point of reflected indifference occurs at day 33 and continues through day 61 in 1993 and days 21 through 41 in 1994. Figure 3.3 (1991) and Figure 3.5 (1992) illustrate that fishers do not have a clear preference for either prawn species after the point of reflective indifference. This point of reflected indifference has major implications for the fishery, especially if it can be shown that it is related to the movement in the relative abundance and price of the two species. The data used in this thesis do not include a prawn price series. Therefore, the effect of product prices or revenue on switching behaviour cannot be tested. The point of reflected indifference is, however, likely to reflect relative expected catch because relative prices of the NPF fishery product rarely change significantly within a season (Pascoe & Whitman 1995).

3.6.4 Summary Statistics on Individual Boat Participation

Individual boat participation is defined in terms of boat residence and the share of the total number of fishing days. The boat participation rate measures the proportion of days a vessel actually resides in a fishery. Over time, one can show the percentage of licensed time that is spent in the banana prawn season compared to the tiger prawn season. The number of times a vessel is used in a fishery may depend on a range of factors including:

- the cost structure of the fishing firm,
- the risk-taking behaviour of the skipper,
- gear restrictions imposed by fishery management,
- the number of vessels owned by skippers,
- skipper characteristics,
- fleet structure, namely, the proportion of owner-operated vessels and company-owned vessels, and;
- the equalisation of expected marginal cost and expected marginal revenue, and
- disinterest in utilising the full provisions of the licence[30].

[30] For operational reasons, it may be in the interest of fishing firms to opt for a longer season than is optimal.

Boat breakdowns can often contribute significantly to lower boat participation rates[31]. In addition, change of ownership may affect the activities of the vessel. Similarly, firms that have more than one boat may choose to keep a vessel idle in order to generate some spare capacity depending on the level of fishing. Such semi-retired boats may be re-launched when larger than usual prawn catches are reported, provided their licences are valid.

A range of indices reflecting individual boat participation has been calculated. The indices include the rate of participation of a vessel in a given fishing period. For example, in 1992 the season was open for 229 days, with 81 days of fishing restricted to the first half of the season and the remainder (148) allocated to the second half of the season. If a vessel searched for 152 days over the entire fishing season, then the vessel's rate of participation is 66 percent. The share participation can also be expressed as the number of boat-days each skipper (vessel) resided in a fishery as a percentage of the total, mean and median number of days respectively. The participation rate and other related indices are not reported in this thesis since they reflect the preferences and fishing patterns of each vessel participating in the fishery[32]. It is useful, to point out, that the rate of participation by individual vessels is fairly high.

3.6.5 Summary Statistics on Fishers' Ground Choice Decisions

The results for fishers' spatial preference for fishing grounds are summarised in Table 3.13. Table 3.13 shows the descriptive statistics for fishers' ground choice during the period 1991 through 1994. These descriptive statistics include the mean, minimum and maximum number of fishing grounds visited during each fishing period in 1991 through 1994. In addition, measures of shape and peakedness of distribution of ground choices are presented.

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[31] A longer season may accord the vessels the flexibility to re-enter the fishery in the event of a breakdown.

[32] The data are confidential and the Deed of Declaration precludes the detailing of these findings.

The results show that the average number of fishing grounds targeted during the banana prawn season in 1992 and 1994 was lower than that for the tiger prawn seasons of 1992 and 1994. For example, on average, skippers searched in 13 grounds in the 1992 tiger prawn season, compared to 8 during the banana prawn season. In general, most skippers tend to search in more fishing grounds during the tiger prawn season, than during the banana prawn season. The large standard deviations and range displayed in Table 3.13 are, however, noteworthy. The differences in the means of fishers' ground choice during the banana and tiger prawn seasons are, however, not statistically significant at the 5 percent level. Frequency distributions and ogive curves for fishers' ground choices are shown in Figures 3.11 through 3.18.

TABLE 3.13 Descriptive Statistics for Ground Choices during the Tiger Prawn Season (TPS) and Banana Prawn Season (BPS), in 1991 through 1994

	1991		1992		1993		1994	
Statistic	BPS	TPS	BPS	TPS	BPS	TPS	BPS	TPS
Mean Number of Grounds Visited	11.865	11.651	8.347	12.148	11.92	11.74	9.254	11.865
Standard Error (SE)	0.34	0.352	0.349	0.322	0.451	0.322	0.416	0.34
Median	13	12	8	13	12	12	8.5	13
Mode	13	15	5	13	9	12	7	13
Standard Deviation (SD)	3.819	4.621	4.516	4.183	5.04	3.63	4.67	3.819
Variance	14.582	21.351	20.397	17.496	25.397	13.178	21.807	14.582
Kurtosis	0.011	-0.312	0.419	0.084	0.43	0.765	-0.888	0.011
SE Kurtosis	0.428	0.368	0.374	0.371		0.427	0.428	0.428
Skewness	-0.489	-0.109	0.704	-0.3	-0.035	-0.767	0.343	-0.489
SE Skewness	0.216	0.185	0.188	0.187	0.217	0.215	0.216	0.216
Range	19	24	25	22	21	18	19	19
Minimum	2	1	1	1	1	1	1	2
Maximum	21	25	26	23	22	19	20	21
Sum	1495	2004	1394	2053	1490	1491	1166	1495
Valid	126	172	167	169	125	127	126	126
Missing	0	0	0	0	0	0	0	0

Figure 3.11 Fishers' Ground Choices in 1991 Fishing Period

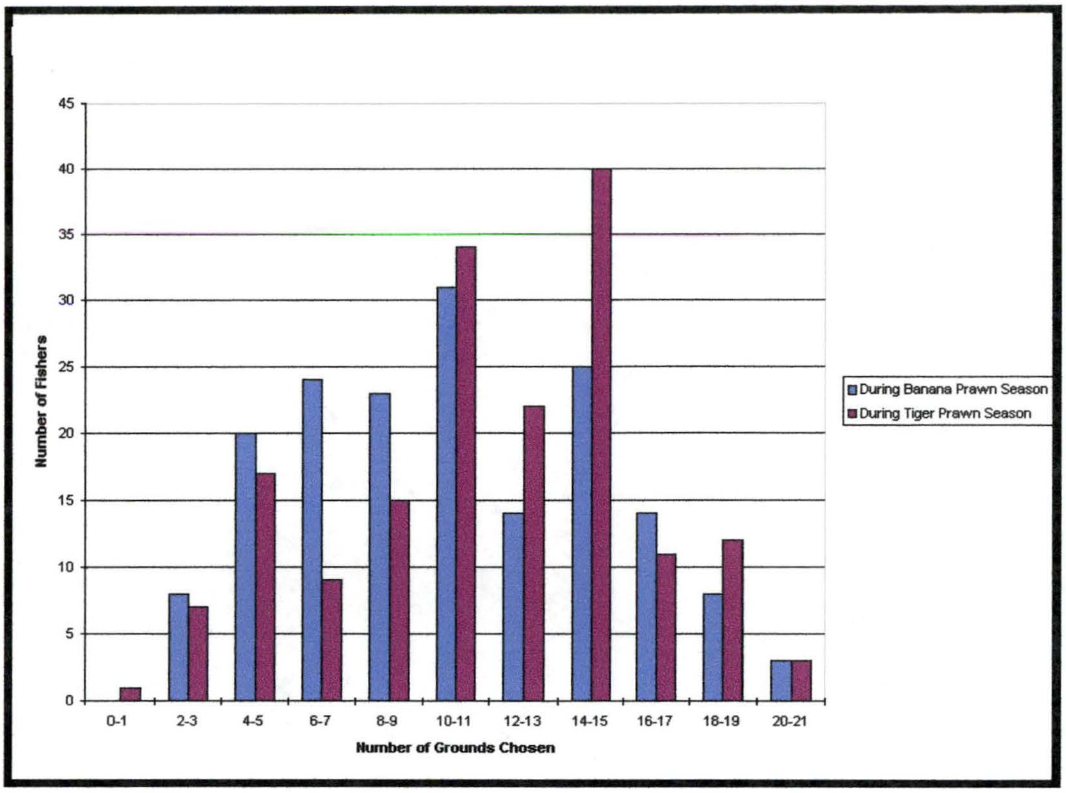


Figure 3.12 Ogive Curves for Fishers' Ground Choice in 1991 Fishing Period

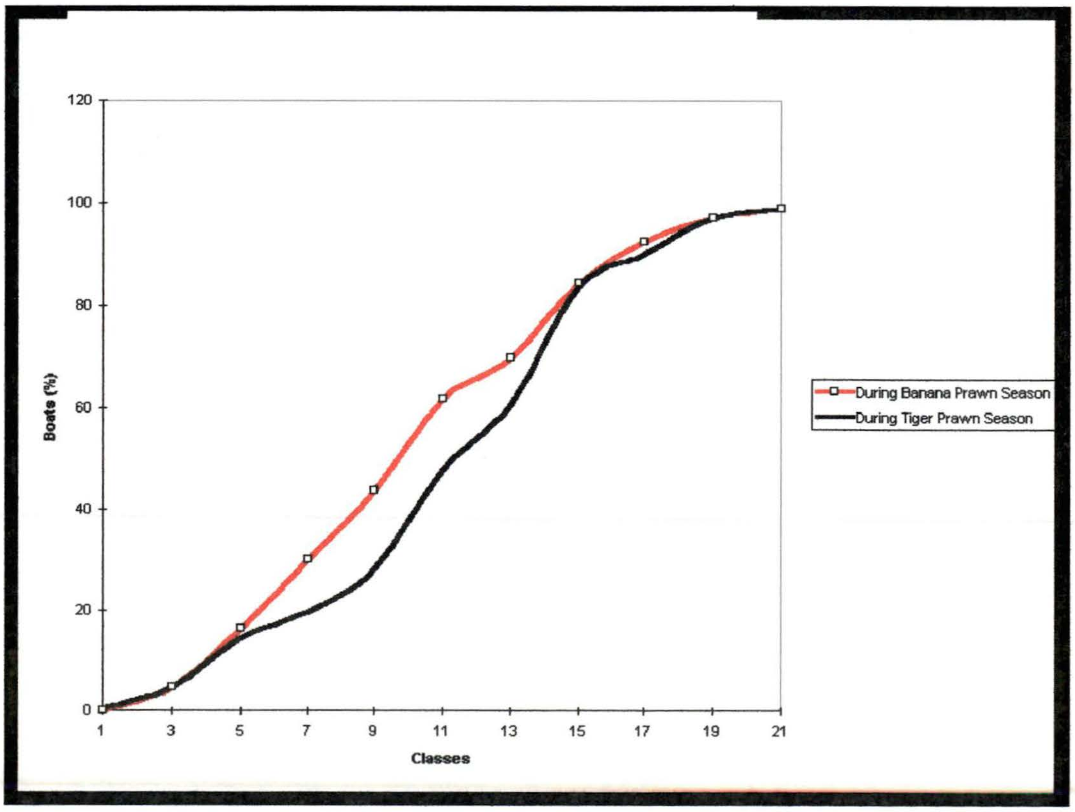


Figure 3.13 Fishers' Ground Choices in 1992 Fishing Period

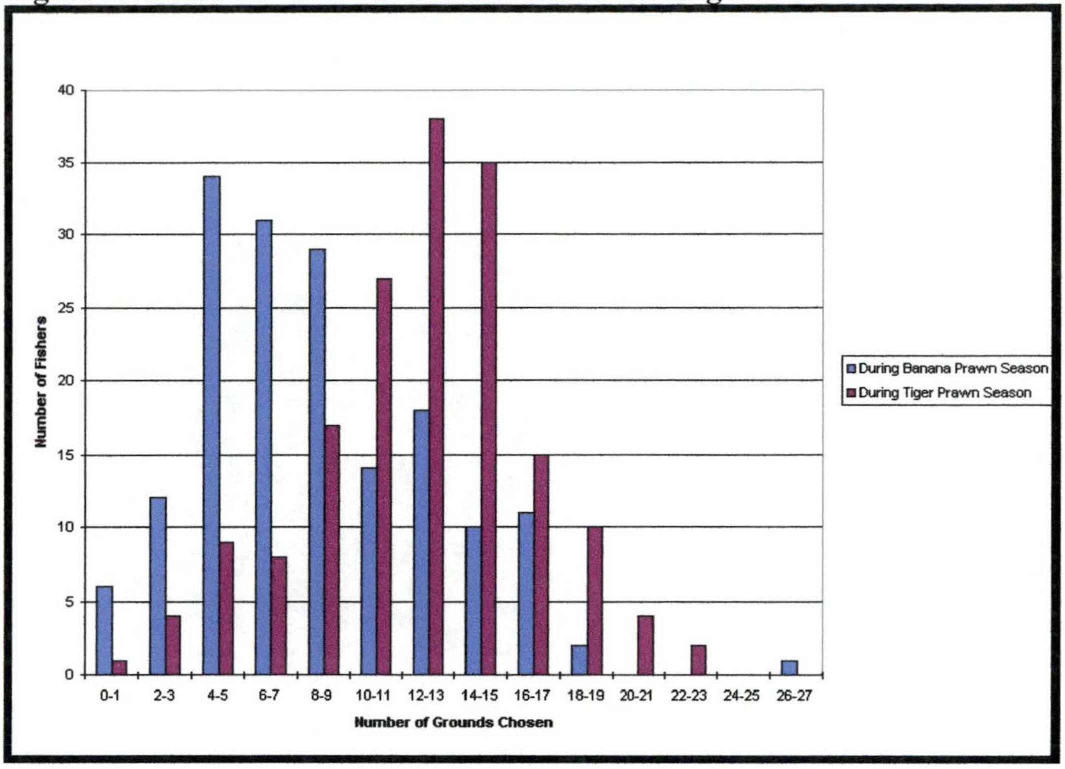


Figure 3.14 Ogive Curves for Fishers' Ground Choice in 1992 Fishing Period

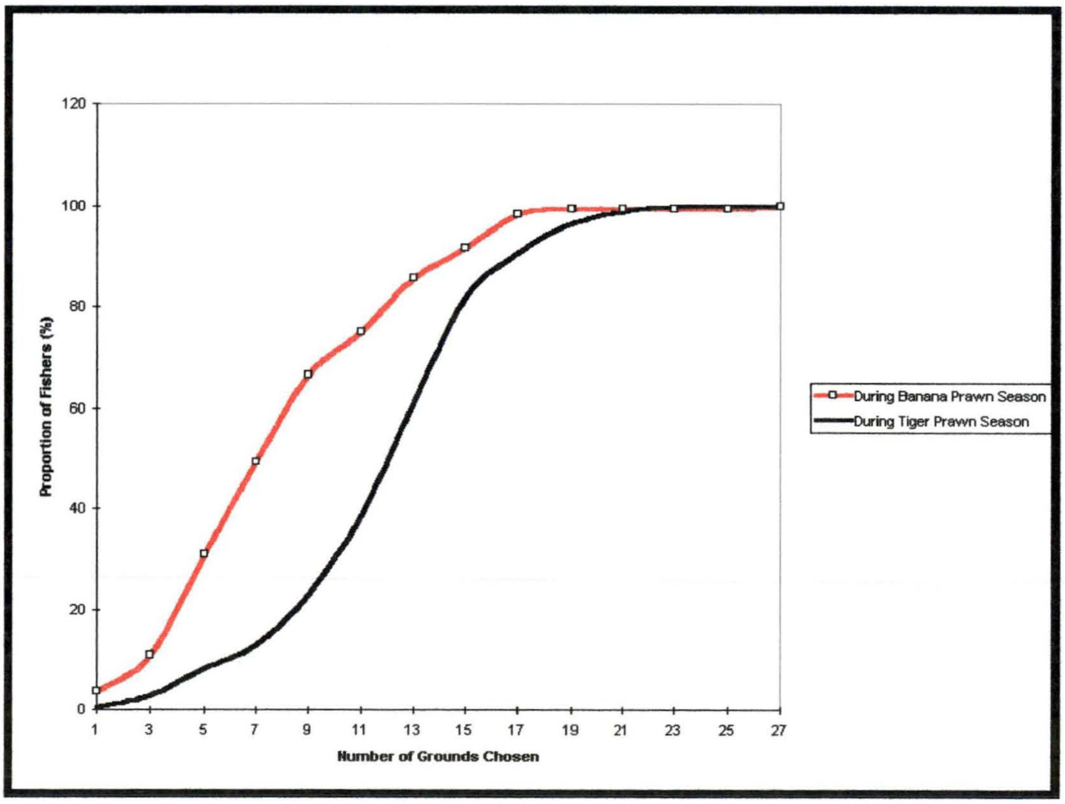


Figure 3.15 Fishers' Ground Choices in 1993 Fishing Period

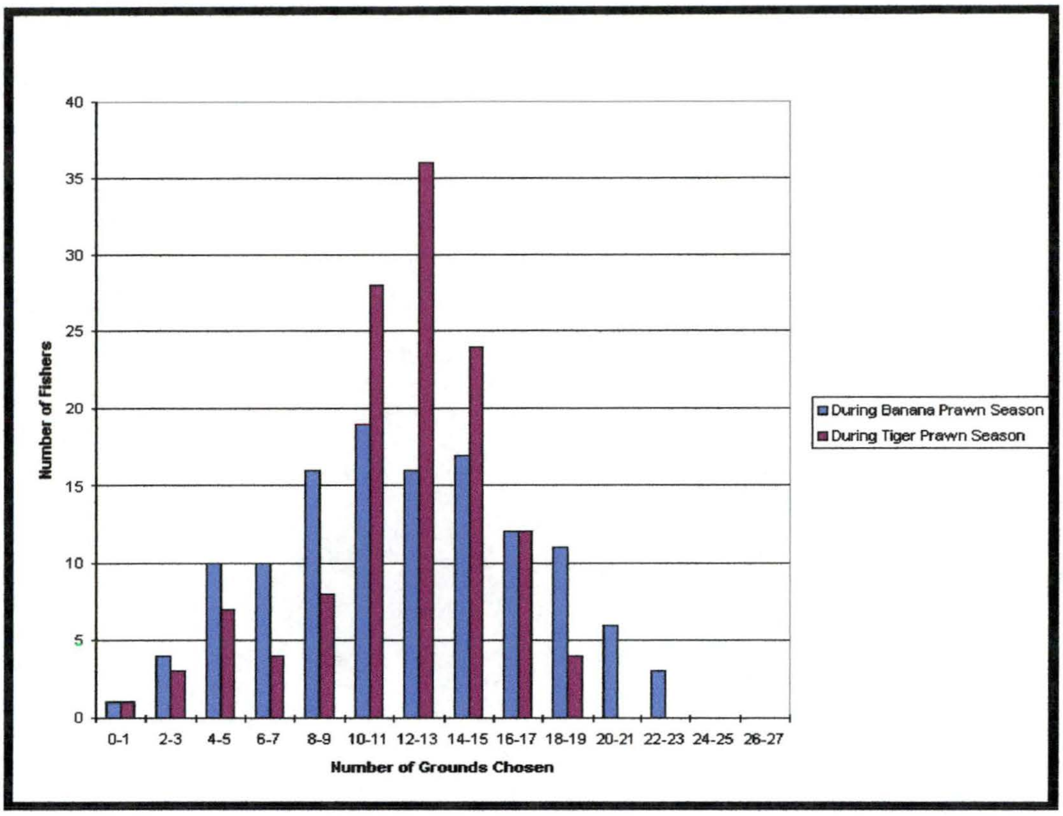


Figure 3.16 Ogive Curves for Fishers' Ground Choice in 1993 Fishing Period

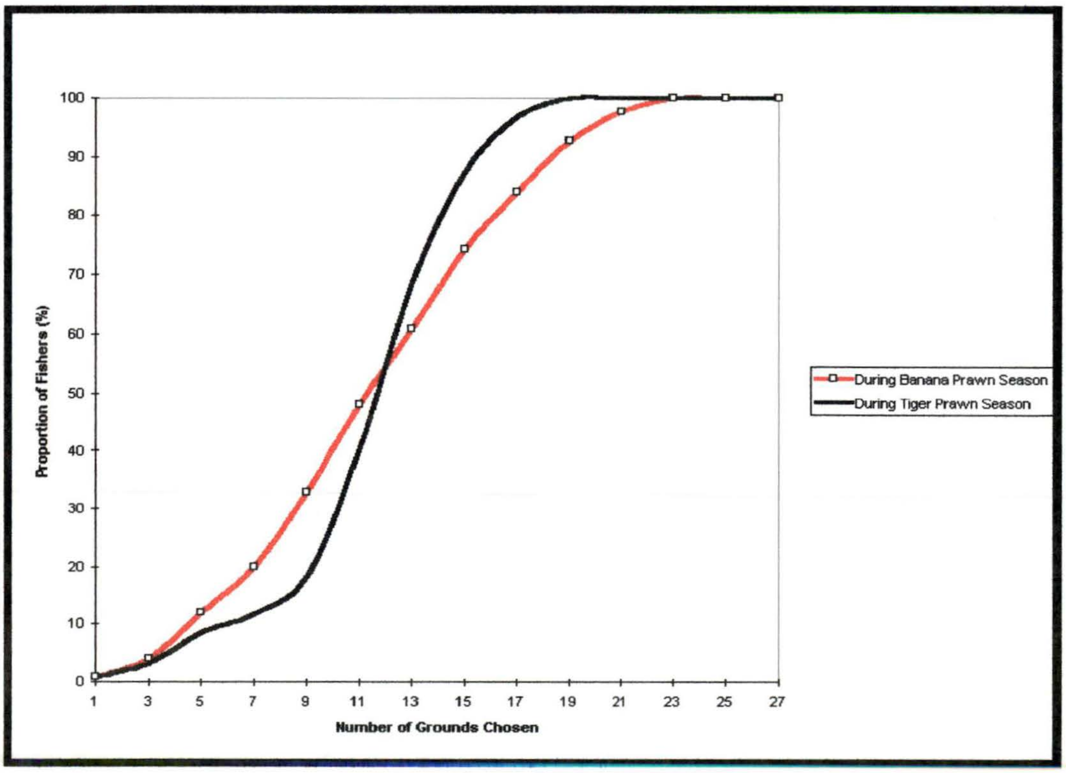


Figure 3.17 Fishers' Ground Choices in 1994 Fishing Period

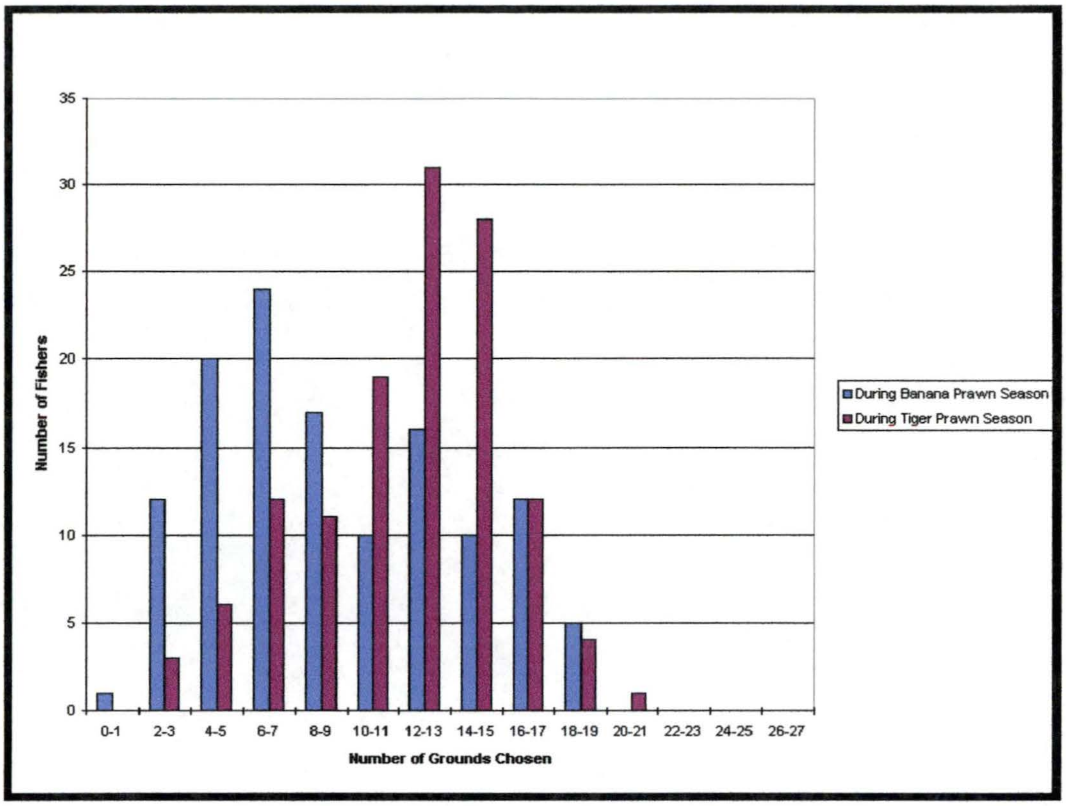
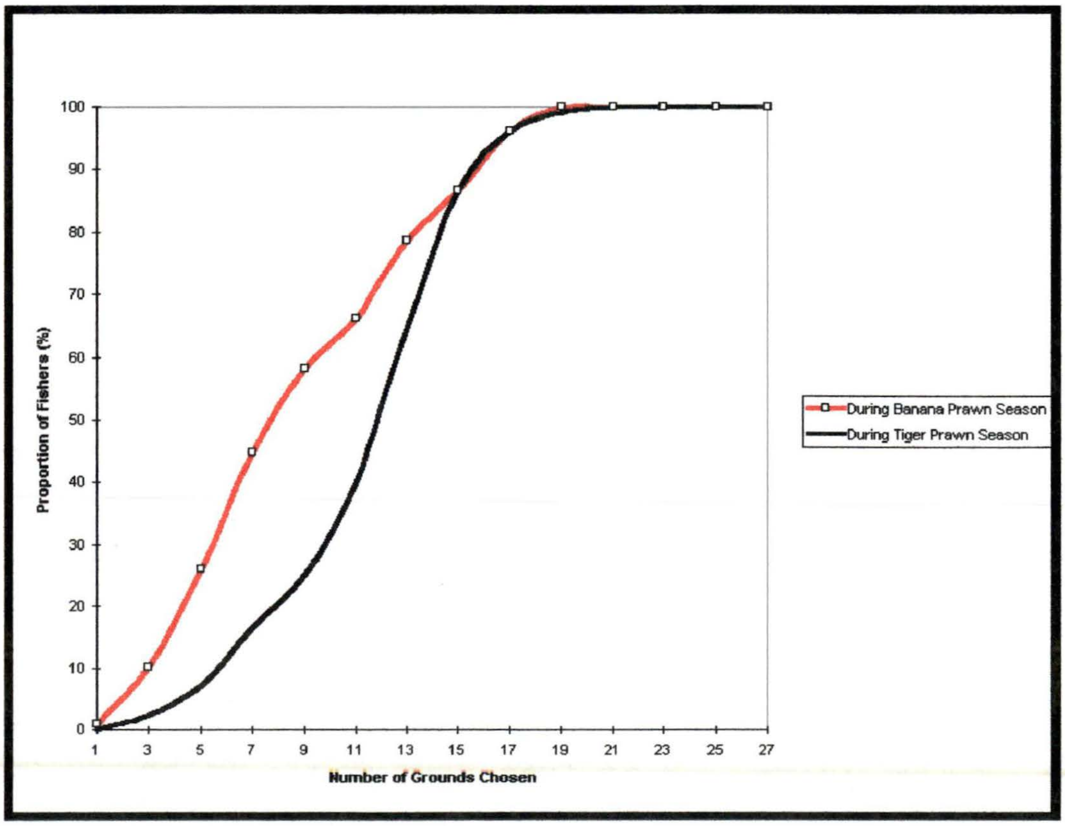


Figure 3.18 Ogive Curves for Fishers' Ground Choice in 1994 Fishing Period



3.7 Fishing Power in the NPF

The NPF data set does not include variables such as hold capacity, engine size and crew size. These variables are key determinants of fishing power. These data were not available to the researcher to make an independent assessment of fishing power so reference must be made to empirical findings on fishing power in the NPF by Robbins, Wang and Die (1996, 1998)[33].

Robins, Wang and Die (1996) investigated the impact of GPS and plotter system on the relative fishing power of the NPF fleet. Their study focused mainly on the tiger prawn fishery. Using commercial data, Robins, Wang and Die (1996, 1998) determined the fishing power of each trawler based on boat length, length of main trawling gear, number of years the fisher has used a plotter unit, and the presence or absence of GPS and plotter units. Robins, Wang and Die (1996, p.10) used the following model:

$$\begin{aligned}\log C_{ijkt} &= \alpha_0 + \alpha_1 \log g_{ik} + \alpha_2 \log l_i + \\ &\quad \beta(X_{ik}) + \delta \log E_{ijkt} + \log h(N_{jkt}) + \varepsilon_{ijkt}\end{aligned} \tag{1}$$

where ε_{ijkt} is the error term, C_{ijkt} is catch of the ith boat in area j during year k and month t, α_0 is the intercept, α_1 is the gear effect, g_{ik} is the fishing gear variable, α_2 is the length effect, l_i, is the length of the fishing vessel, X_{ik} is the GPS category for a boat, $\beta(X_{ik})$ is the effect of GPS category, E_{ijkt} is fishing effort, $h(N_{jkt})$ is an unknown abundance function, and δ is an unknown parameter that generalises a fishing mortality function (Robins, Wang & Die 1996, p.7; Robins, Wang & Die 1998, p.1647). The parameters and standard errors for the generalised linear model of Robins, Wang and Die (1996) are shown in Table 3.14

[33] Detail on the generalised linear model is presented in Robbins, Wang and Die (1996, 1998). I wish to acknowledge the detailed personal communication with Carolyn Robbins and David Die on the subject.

Table 3.13 Fishing Power in the NPF

Variables	*Parameter*	*Estimate*	*Standard Error*
Effort	δ	1.067	0.005
Average headrope length	α_1	0.566	0.022
Average boat length	α_2	0.399	0.03
GPS but no plotter	β_{100}	0.037	0.01
GPS and plotter during year 1 of fisher's experience	β_{111}	0.068	0.008
GPS and plotter during year 2 of fisher's experience	β_{112}	0.091	0.009
GPS and plotter during year 3 of fisher's experience	β_{113}	0.123	0.011

Source: Robins, Wang and Die (1996)

Robins, Wang and Die (1996) concluded that:

- the inclusion of a GPS unit without a plotter resulted in a 4 percent increase in relative fishing power over boats without a GPS,
- the joint use of a GPS unit and a plotter unit raises the relative fishing power to 7 percent.
- An additional 2 or 3 percent increase in relative fishing effort occurs each year after the first, second and third year that a skipper has been working with a plotter.
- When all boats had GPS and plotter systems and all fishers had at least three years experience then the fishing power of the fleet would have increased by 12 percent.

Robins, Wang and Die (1996, 1998) argued that it appears that further effort controls will need to be considered in order to maintain the desired levels of effort in the NPF.

3.8 Implications for Fisheries Management

The following are the main implications of these findings. First, the data demonstrate that the search for tiger prawns is mostly likely to be random in some fishing grounds, and systematic in others. This factor must be considered in developing a spatial and temporal model of the allocation of tiger fishing effort. Second, since search for tiger prawns can be modelled as continuous search, then the fisher's decision can also be modelled in terms of deciding whether to search and fish outside or within the most preferred fishing ground. Fishers searching predominantly outside the most favoured fishing grounds can be modelled without much need to accommodate congestion externalities as well as the effect of "fishing news" of search and fishing behaviour. If it can be shown that mean catch per boat is the same within and outside the most favoured ground, then for fishers capable of fishing in the most preferred fishing ground who, however, decide to fish outside they may be insensitive to fishing news. It is also possible that such fishers may value the avoidance of congestion externalities highly, and they may display a particular type of herd behaviour quite contrary to the one dictated exclusively by the most preferred fishing ground –"hotspots". Finally, the analysis of tiger search may be more focussed if an explicit model is developed for the dynamics of entry and exit of skippers from the common grounds. This reduces the complexity of the search model in the sense that group interaction is modelled only in selected grounds and activity elsewhere is modelled as independent.

3.9 Concluding Remarks

An understanding of the process of fishing is important in fishery management because it can serve as an aid in evaluating fishers' reaction to management policies. A detailed description of search and harvesting patterns for banana and tiger prawns in the NPF has been presented in this chapter. It is important to note that the discussion focuses on these two main commercial species of prawns. There are, however, other species of prawns caught in the NPF when fishers trawl for banana and/or tiger prawn species. In this chapter search patterns are not distinguished from harvesting, although such a distinction is potentially of value in evaluating search for species other than tiger prawns[34]. Search for and harvesting of tiger prawns can be modelled as a continuous stochastic processes. Observed search patterns are determined by fishers' decisions regarding where, when and for what to fish. These decisions are conditioned by the fishers' information endowment, including historical patterns of vessel movements, the motivation of profit or revenue maximisation, the imperative of competitive and/or cooperative behaviour (or information sharing) and the dynamics of stock recruitment.

The theoretical argument is that the efficient acquisition, processing and use of fishing information on spatial and temporal concentration profiles of prawns, characteristics of fishing zones, search patterns of competing and/or cooperating vessels, and other factors, can lead to higher catches and improve fleet revenues. The process of fishing is a joint production process that yields information on stock levels, and catch in particular fishing grounds. The major decision problems which search patterns are likely to reflect concern which SFZ and ground fishing should take place in, where and for what to fish in the selected zone or ground, when and how to relocate to the various grounds in a SFZ, how much time to allocate for exploratory search, the size of stocks to pursue, signals required to induce relocation and the extent to which fishers must cooperate, compete and/or trade in fishing information. Fishers' choices of fishing grounds are likely to be based on incomplete information about the net returns or potential catch from the selected SFZs. The range of variables that fishers have to deal with is quite large. It is reasonable to argue that fishers use, therefore, the best information available to them.

[34] The data available do not enable such a distinction to be made in this thesis.

CHAPTER 4

ANALYTICAL FRAMEWORK

4.1 Introduction

The main objective in this chapter is to develop a theoretical framework for describing fisher behaviour that can be used to explain and forecast fleet dynamics. In this framework the activities of searching for, and harvesting fish are treated as comprising a chain of related events. The theoretical structure of the model presented in this chapter draws on expositions of the theory of stochastic processes given by Bellman (1954, 1957), Bharucha-Reid (1960), Howard (1960, 1971a, 1971b), Billingsley (1961, 1986), Bailey (1964), Bartholomew (1967), Bartos (1967), Martin (1967), (Feller 1968), Bhat (1972), Basawa & Rao (1980), and French (1986), among others. This theoretical structure is used to develop a Markovian fleet dynamics model for the NPF.

The essential concepts and definitions used in the Markov fleet dynamics model are presented in Section 4.2. A characterisation of the fisher's searching and harvesting activities as a Markov process with net rewards is presented in Section 4.3. A description of Markovian fleet dynamics is presented in Section 4.4. Statistical estimation and inference of transition parameters are outlined in Section 4.5. A framework for explaining transition probabilities is provided in Section 4.6. In this section transition probabilities are explained using both the multinomial logit (MNL) and seemingly unrelated regression (SUR) models. The MNL model (Greene 1990, 1993) presented in Section 4.6.1 is focused mainly on explaining time-invariant ground choice. This is followed, in Section 4.6.2, by a discussion of a SUR model (Judge et al. 1985, 1988) is used to explain time-varying fleet transitions. Concluding remarks are drawn in Section 4.7.

4.2 Markov Chain Modelling

In Markov chain modelling, activities and/or processes are thought of as chains of events, in which movement from one state to another occurs at each step. Usually it is not possible to predict exactly which way a process will move at any given step, but it is possible to express such movement in terms of the probability of transition at each step. The transition probabilities used in describing step-by-step movements are generally influenced by, and form part of, the decision-making process. A process where probabilities are involved in describing step-by-step movements is called a stochastic process and a mathematical description of the process is a stochastic model. The essential ingredients of a stochastic process are, therefore, sets of states and probabilities for state-to-state movements or transitions. Either the state or the probability rule for determining the state must be known.

The observed transitions between states indicate the probability of relocating between any two states over a specified time interval. In this thesis, it is argued that these transition probabilities are endogenous and that they display the Markov property. The Markov property requires that the probability of a particular transition occurring at the next step depends only on the present state of the process and not on any preceding states occupied.

The observed movement of a process among its set of states may be used to compute the following. First, the probability that the process will be in state s_j after n steps given that it began in s_i can be computed. Second, the expected number of times the process will be in a given transient state can be determined. Third, the mean and variance of the number of steps taken in moving from state s_i to state s_j can be calculated. Finally, the mean and variance of the number of states entered in a given period can be specified.

Clearly, relocation between any two states may occur in any number of steps. If any state can be reached by relocating from any other state, then the transitions are referred to as ergodic. The probability of a process passing from one state to another in exactly n steps is called an n-step transition probability, and the resultant Markov chain is an n-step ergodic Markov chain.

Assuming that there are m states in a process, the probability of a transition from s_i to s_j, in two steps, $p_{ij}^{(n=2)}$, is the sum of the probabilities $p_{i1}p_{1j}$, $p_{i2}p_{2j}$, ... , $p_{in}p_{nj}$.

Therefore,

$$p_{ij}^{(n=2)} = \sum_{r=1}^{n} p_{ir}\, p_{rj} \tag{1}$$

It follows that

$$p_{ij}^{(n+1)} = \sum_{r=1}^{n} p_{ir}\, p_{rj}^{(n)} \tag{2}$$

and this expression holds for any integer n, by induction. The probability that the state of the process after n steps is s_j will be denoted by $a_j^{(n)}$. This probability is an absolute (or unconditional) probability. It may be shown as follows:

$$a_j^{(n)} = \sum_{r=1}^{n} a_r\, p_{rj}^{(n-1)} \tag{3}$$

where, a_r are the initial state probabilities. Each term in the sum is the product of the probability that the first state is s_r and the probability that the process moves from s_r to s_j in the first n-1 steps. It is clear that $a_j^{(n)}$ is the j^{th} element of the row vector formed by multiplying **a** by $\mathbf{P}^{(n-1)}$, where **a** is a vector of initial state probabilities, **P** is the transition probability matrix and $\mathbf{a}_n$ is the vector of destination state probabilities. If a_n is the row vector $a_j^{(n)}$ then $\mathbf{a}_n = a\mathbf{P}^{(n-1)}$, for all $n > 1$, $a_1 = a$.

The fundamental theorem of a Markov chain states that, regardless of the starting state of the process, the probability of being in a given state of the regular chain tends to some constant value as the number of steps from the start becomes larger (Takacs 1960; Prabhu 1965; Taha 1971; Kemeny & Snell 1976; Iosefescu 1980). That is, for any regular transition matrix, then over time the Markov transition matrix tends towards the constant transition matrix, ***B***. The rate of convergence of elements of a Markov transition matrix to a limiting (constant) value is very rapid, and the limit is often approached geometrically (Turner 1970)[1]. The resulting matrix, **B**, is commonly referred to as the stochastic matrix (Whittle 1955; Martin 1967).

[1] In many applications or examples the approximation $P^5 \simeq B$ will be found to be very good (Turner 1970).

The probability vector **B** is called the limit vector or stationary probability distribution of the Markov chain. This limit is the observed probability of movement throughout the selected time period. These limiting values form the stationary probability distributions of the Markov chain. Movement between states over a period of time can be modelled, therefore, in terms of the limit vectors of a regular Markov chain matrix.

4.3 Markov Chain Modelling of the Fishing Process

A fishing system can be looked at in terms of transitions between fishing grounds where fishing grounds denote the states. The movement between fishing grounds, over time, reflects temporal and spatial searching for and harvesting of fish. Fishers allocate their endogenous effort in response to a reward or return structure. Therefore, a Markov chain model with rewards captures the fisher's reward optimisation problem and the spatial aspects of the fishing process. In this thesis, the fisher's process of effort allocation is modelled as a Markovian renewal process with rewards. The states in this renewal process represent the spatial dimension of fisheries search and production, and the rewards are catches. Since the spatial allocation of effort occurs over the entire fishing season, the Markovian renewal process also represents the temporal aspects of the fishing process.

The fisher is assumed to specify a search-harvesting policy for all states and all time periods (stages). This policy represents the set of decisions made at each time period. The derivation of the fisher's optimal policy is given in Section 4.3.1. The fisher's optimal policy is one that maximises total expected return from the fishing grounds visited over the fishing season. When population growth and catches are known in each ground the return is given by

$$V_i(t+1) = \max \sum_{t=1}^{T} p_{ij}\left[R_{ij} + V_j(t)\right] \tag{4}$$

where

i,j	-	the set of fishing grounds defining the system, i,j = { 1,2,..., m);
m	-	the number of fishing grounds;
t	-	number of time periods in fishing renewal process t= {1,2, ..., T},
R_{ij}	-	the net reward associated with the transition from ground i to j,
V_i (t)	-	the total reward for a fisher in state i, at time t, and
p_{ij}	-	the probability of transition from ground i to j

Note that for each transition made by the fisher, there is an associated cost. In Gordon (1954, p.130) the cost of fishing supplies are assumed to be unaffected by the amount of fishing effort. However, cost information is not routinely collected in fisheries (Ward & Sutinen 1994, p.919). In general, it is assumed that all the transitions have known costs. Assuming that fishing in the fishery involves constant cost and constant output price, it is appropriate to focus on catch, since the constant cost-constant price condition implies that the fisher maximises net revenue when catch is maximised. In modelling short-run fishing behaviour in the NPF it is assumed that costs are constant (Haynes & Pascoe 1988, p.32). It is assumed, therefore, that fishers compare expected returns in all states before choosing the expected catch-maximising state. The expected return, Q_i, from a single transition from state i for fisher, can be expressed as

$$Q_i = \sum_{j=1}^{m} p_{ij} R_{ij} \qquad (5)$$

Assuming that the process is ergodic then, for the limiting state probabilities of the Markov process, Q_i represents the expected gain to the fisher of moving from one state to any other.

4.3.1 Markov Chain Reward Model without Discounting

A mean return, R_{ij}, is associated with all transitions from fishing ground i to fishing ground j. For each fisher the cumulative reward in the next transition, given that the system is in state i at present, $V_i(t)$, is given by

$$V_i(t+1) = \sum_{j=1}^{m} p_{ij}[R_{ij} + V_j(t)], \forall i, j = 1,2,\dots,m \tag{6}$$

The expression for the future cumulative reward can be rewritten in the form

$$V_i(t+1) = Q_i + \sum_{j=1}^{m} p_{ij} V_j(t) \tag{7}$$

where

$$Q_i = \sum_{j=1}^{m} p_{ij} R_{ij} \tag{8}$$

For the different time periods or stages a recursive relationship that defines an iterative procedure for determining the optimum relocation decision can be derived using a standard technique in dynamic programming. This iterative procedure yields a result that converges to the best alternative the fisher can expect to obtain from each fishing ground over time (Bellman 1954, 1957). Since the procedure is based on the value of the policy that leads to the maximum cumulative return at any fishing period, the procedure is called the value-iteration method. The method is based on determining, recursively, the optimum policy at every stage or time period (Howard 1960, pp. 32-75).

The recurrent relationship used is

$$\begin{aligned} V_i(t=1) &= Q_i + \sum_{j=1}^{m} p_{ij} V_j(t=0) \\ V_i(t=2) &= Q_i + \sum_{j=1}^{m} p_{ij} \left[Q_i + \sum_{j=1}^{m} p_{ij} V_j(t=0) \right] \\ &= Q_i + \sum_{j=1}^{m} p_{ij} Q_i + \sum_{i=1}^{m} \sum_{j=1}^{m} p_{ij} p_{ij} V_j(t=0) \\ &= Q_i + \sum_{j=1}^{m} p_{ij} Q_j + \sum_{k=1}^{m} p_{ij}^2 V_j(t=0) \end{aligned} \tag{9}$$

In matrix notation, this expression is

$$V(t=2) = Q + PQ + P^2(t=0) \tag{10}$$

Generalising this relationship yields[2]

$$V(t) = Q + PQ + P^2Q + \dots P^{(t-1)}Q + PV(t=0) \tag{11}$$

The equations presented above and used for describing the fishing system require the decision maker to have estimates of P and R. These estimates may be fixed over a set time interval (in which case they are referred to as limiting transition probabilities and rewards, respectively). In cases where P and R may change over time, the terms time-varying transition probabilities and time-varying rewards are used, respectively.

For deterministic population growth and catches the fisher's optimal policy that maximises overall expected return from a fishing system is given by

$$V_i(t+1) = \max \sum_{j=1}^{m} \left[p_{ij} R_{ij} + \sum_{j=1}^{m} p_{ij} V_j(t) \right], \forall \ t = 1,2,\dots,T; i = 1,2,\dots,m \tag{12}$$

This states that the level of the reward in time period t+1 is a sum of all past rewards, up to time t, and the product of receiving present reward R and its probability.

4.3.2 Markov Chain Reward Model with Discounting

The mathematical model of the Markovian reward process can be structured so as to include the discounting of the value of the reward. Suppose τ is the discounting factor for a transition interval and that $(0 < \tau < 1)$. An economic reward obtained at the beginning of the transition period will be worth only τ units at the end of the transition period. Accounting for discounting gives rise to the recurrence relationship

$$\begin{gathered} V_i(t+1) = \sum_{j=1}^{m} p_{ij}\left[R_{ij} + \tau V_j(t)\right] = Q_i + \tau \sum_{j=1}^{m} P_{ij} V_j(t), \\ \forall \, i = 1,2,\dots,m; t = 1,2,\dots,T \end{gathered} \tag{13}$$

[2] The generalisation of this function that includes the limiting probability distribution is detailed by Bhat (1972, pp.189-190).

where, V_i (t) is the expected total earnings for t transition periods during which the Markov chain operates with a transition probability matrix P and a reward matrix R, and a constant discounting factor τ.

Expressing these equations in matrix notation and solving the equation recursively yields

$$
\begin{aligned}
V(t=1) &= Q + \tau P(t=0) \\
V(t=2) &= Q + \tau PQ + (\tau P)^2 V(t=0) \\
. &= . \\
. &= . \\
. &= . \\
V(t) &= Q + \tau PQ + (\tau P)^2 + \ldots + (\tau P)^{t-1} Q + (\tau P^t V(t=0))
\end{aligned}
\tag{14}
$$

Howard (1960, 1971a, 1971b), Derman (1970), Bhat (1972) and Heyman and Sobel (1982, 1990) show that when the discount rate is constant, in contrast to the non-discounting case, the expected future earnings of the process do not necessarily increase over time. The optimal policy in a Markov process with discounted rewards is sensitive to the discounting factor and independent of the time interval. The system of equations presented above is consistent with a Markov fishing system in which the fisher's choice of a fishing ground is conditional on information obtained from the fishing ground visited most recently, and the accumulation of the reward to date.

4.4 Markovian Fleet Dynamics

The discussion presented in Sections 4.1 through 4.3 has detailed the use of transitions in a Markov system. The transitions have been related to a deterministic ground-based fishery reward system. In this section, attention is drawn to accounting for the variation in transition probabilities. This will set the scene for addressing the following questions. In a fishery management system, what might the transition probabilities depend on? Is there a system of equations that can be used to explain the reward structure? Of what relevance is rational behaviour in searching and harvesting? What are the likely effects of rational fishing behaviour on selected fisheries management techniques, and vice versa?

It is reasonable to argue that rewards are themselves subject to random variation and that the expected reward and the variance of the reward, among other things, condition the deployment of vessels and, therefore, vessel transitions. Such transitions result from complex social and behavioural processes that are influenced by random events.

The main premise in developing the framework in this thesis is that searching and harvesting behaviour of the fishing fleet can be modelled as a Markov chain. At a practical level this requires the following:

- there is a well-defined finite set of fishing grounds (or states) in a fishery;
- the selected time period is relatively short, such that a fisher can fish in only one fishing ground during the given time period;
- there is a fixed number of fishers in the fishery (a limited entry regime achieves this) during the fishing period, and;
- the fishing system is observed at regular intervals, say daily or weekly.

The data required to implement the Markovian modelling framework include the number of fishers changing fishing grounds during any time interval as well as the spatial and temporal distribution of the fleet. Past and current movements are represented using initial starting vectors, destination vectors and transition probabilities. In addition, data on the catch history is needed for evaluation of rewards and for verification of the optimal policy and, therefore, decision rule.

In general, the number of times fishers occupy a *j*th fishing state, n_j, has a geometric distribution and the mean and variance of n_j are given, respectively, by

$$E[n_j] = \frac{1}{1 - p_{jj}}, \tag{15}$$

and

$$V[n_j] = \frac{p_{jj}}{(1 - p_{jj})} \tag{16}$$

$E[n_j]$ is, therefore, the average number of time periods that the fleet or group of fishers will spend in fishing ground j. This measure yields information on the spatial mobility of groups of fishers or the fleet as a whole.

Where the management regime, recruitment of fish stock, and searching and harvesting strategies have not changed significantly over a period of time, then the transition probability matrix is given by the limiting probability distribution of the Markov chain under investigation. If the non-limiting probabilities do not diverge significantly from the limiting probabilities, then the distribution of the fleet can be characterised using the limiting probabilities over the selected time interval, suggesting that, given the manner in which ground choices are made, effort is relatively stable. Since the vector of limiting probabilities is given by π, then these limiting probabilities can be used as a proxy for stability of fleet dynamics. For this limiting transition probability matrix, π, occupation times n_j^* have a mean given by

$$E(n_j^*) = \frac{1}{1-\pi_j} \tag{17}$$

where, n_j^* is the number of fishers in the jth fishing ground when the transition probabilities for the fishing ground, π_j, are limiting transition probabilities. The ratio of the mean occupation times $E(n_j)$ and $E(n_j^*)$ is given by

$$\frac{E(n_j)}{E(n_j^*)} = \frac{(1-\pi_j)}{(1-p_j)} \tag{18}$$

This ratio may be used to proxy the stability of vessel movement[3]. It should be noted that while the probabilities of occupying different states are not the same, they are stable and independent. Such stability implies that the proportion of fishers in different fisher groups remains the same but that fleet mobility is independent of the present state.

A different indicator of vessel mobility, based on the expected number of states entered in one transition, can be developed from Bartholomew (1967). Assuming that the system is in a state of equilibrium and the limiting probability distribution of the groups of boats is given by π_j, j = 1,2, ... ,m, the expected number of states entered in one transition, D, is given by

[3] Similarly the ratio p_{jj}/π_j can be considered an indicator of the stability of vessel mobility.

$$D = \sum_{i=1}^{m}\sum_{j=1}^{m}\pi_i p_{ij}\,|i-j| \qquad (19)$$

Bhat (1972, p.298) argued, however, that even though this measure is of limited use, it describes mobility better than a measure based on occupation times. In addition, the method for computing D cannot be used for comparing systems with different vessel class structures[4].

4.5 Estimation and Inferences of Transition Parameters

The analytical framework presented requires the use of transition probabilities. It is important to consider the maximum likelihood estimates of the time-dependent and time-independent transition probabilities. These maximum likelihood estimates are presented in Section 4.5.1. Given the discussion on characterising the fishing process as a Markov process, it is prudent to discuss some of the properties of transition data used in the Markov fleet dynamics model. In Section 4.5.2 selected characteristics of transition data are presented. It is also prudent to recall that in the case of Markov fleet dynamics these transition data are generally presented in the form of transition matrices.

Where the transition probability matrices are formed over several time periods they are referred to as intermediate transition probability matrices. An aggregation of intermediate transition probability matrices is called the overall transition matrix, **A**, and consists of all possible transitions probabilities over all defined space and time interval. Intermediate and overall transition matrices are particularly useful in fisheries fleet dynamics given that most fisheries data are collected on a daily or annual basis. In cases where daily and annual fisheries data are used, overall and intermediate transition matrices for each fishing season will be referred to as daily and annual transition matrices, respectively. Selected characteristics of transition probability matrices are presented in Section 4.5.3.

[4] The nature of the data on the NPF analysed in this thesis is such that a vessel can reside in only one fishing ground in one fishing day.

4.5.1 Maximum Likelihood Estimates of Transition Probabilities

The stationary transition probabilities, p_{ij}, also called time-invariant or time homogeneous transitions, can be estimated by obtaining the following maximum likelihood estimates, $\hat{p}_{ij}$ (Bhat 1962; Parzen 1962; Ross 1980; Heyman & Sobel 1982, 1990; Frydman 1984)

$$\hat{p}_{ij} = \frac{n_{ij}}{n^{*}_{i}} = \frac{n_{ij}}{\sum n_{i}} \tag{20}$$

and, subject to the conditions $p_{ij} \geq 0$, and

$$\sum_{j=1}^{m} p_{ij} = 1, \; i = 1,2,\ldots,m \tag{21}$$

When the transition probabilities are not necessarily stationary, the general approach used for stationary transition probabilities can still be applied and the maximum likelihood estimates for the $p_{ij}(t)$ are

$$\hat{p}_{ij}(t) = \frac{n_{ij}(t)}{n^{*}_{i}(t)} = \frac{n_{ij}(t)}{\sum_{j=1}^{m} n_{ij}(t)} \tag{22}$$

The maximum likelihood estimates for the $p_{ij}(t)$ are obtained when using (i) the probability distribution of $n_{ij}(t)$ conditional on $n_i(t\text{-}1)$ and (ii) the joint distribution of the number of transitions between states over time, $n_{ij}(1), n_{ij}(2), \ldots, n_{ij}(T)$) (Parzen 1962; Basawa & Rao 1980). Formally, these estimates are the same as one would obtain if, for each state i and time period t, one had $n_i(t\text{-}1)$ observations on a multinomial distribution with probabilities $p_{ij}(t)$ and with resulting transition numbers, $n_{ij}(t)$ (Parzen 1962; Kemeny & Snell 1970, 1976; Bhat 1972; Basawa & Rao 1980).

The estimates for transition numbers and transition probabilities can be described in the following manner. For a selected time period and given set of states m, the elements $n_{ij}(t)$ are entries in an m x m contingency table. These entries, $n_{ij}(t)$, are particularly useful when conducting goodness-of-fit tests. Anderson and Goodman (1957), for example, presented both the likelihood ratio test and the χ^2 tests and showed how methods of testing goodness of fit in transition probability matrices are related to some ordinary contingency table procedures. The estimate of $p_{ij}(t)$ is the i,jth entry in the table divided by the sum of the entries in the ith row. In order to estimate p_{ij} for the stationary chain, the corresponding entries in the m-way tables for t=1,...,T, are added and a m-way table with entries $\Sigma n_{ij}(t)$ is obtained. The estimate of p_{ij} is the i,jth entry of the table of n_{ij}'s divided by the sum of the entries in the ith row. That is, the estimate of $p_{ij}(t)$ is $n_{ij}(t) / \Sigma n_{ij}(t)$. The estimates of $p_{ij}(t)$ and p_{ij} for situations in which only a single sequence of states is observed generally follow the methods proposed by Bartlett (1950). These methods have implications for (i) testing goodness-of-fit in transition probability matrices, and (ii) assessing the order of the Markov chain (Anderson & Goodman 1957).

The discussion presented above indicates a useful method of estimating transition probabilities and also reinforces the argument that, in estimating the parameters of Markov chain fleet dynamics models, consideration must be given to: (i) the number of fishing grounds (m=1,2,..., m), (ii) observation times (t=0,1,2,...,T) or the fishing time period (T); (iii) the number of vessels making transitions (transition numbers), (v) transition probabilities and (vi) destination vectors. These variables can be considered in either a time-dependent or time-independent framework. It is crucial to point out that time-independence does not necessarily mean constant transition numbers but that the transitions do not depend on time. It is important to make this distinction since it reflects an effort in preserving the stochasticity of transition probabilities.

There are several possible causes of nonstationary behaviour in transition data. In general non-stationarity occurs when $p_{ij}(t) = f(v(t))$ where v(t) may be

a. any exogenous set of variables (Aalen & Johansen 1978; Thornburn 1983; Andersen, Hansen & Keiding 1991),
b. time (Lee, Judge & Zellner 1970; McRae 1977), and
c. a function of the state probability vector (Woolhouse & Harmsen 1987b).

In the case of a fishery system, for the set of fishing grounds M, $p_{ij}(t)$ or p_{ij} are a function of a set of random variables **X** that generally includes characteristics of fishing grounds, the influence of fishery management on fishing activity, fishers' attitudes to uncertainty in allocation of fishing effort, and other related variables. It is maintained throughout the thesis that the set of random variables **X** faced by each fisher determines the transition probabilities P of the Markov chain at any time period. These transition probability matrices still posses the usual properties, namely:

(i) a square matrix with nonnegative elements,

(ii) a stochastic matrix,

(iii) that the Markov chain tends to reach a limiting distribution independent of the initial distribution, and

(iv) the system is ergodic (that is, the fleet can move to any other state regardless of its initial state).

4.5.2 Selected Characteristics of Transition Data

The discussion presented in Section 4.5.1 suggests that in the Markov fleet dynamics framework fishers select a sequence of fishing grounds during the fishing time period. The set of fishing grounds is defined and the maximum possible number of fishing grounds a fisher can occupy over the time interval t to T is m, the fisher can sequence fishing and entry into the defined states in mT possible ways. In the case of the entire fleet these mT possibilities form a set of sufficient statistics for the observed sequences (Anderson & Goodman 1957, p.91). These represent mutually exclusive events with stationary transition probabilities **P** or nonstationary transition probabilities **P**(t).

In representing a fishing system as a Markov process it is important to test the transition data for the following properties: independence, stationarity, linearity, and Markovity. Independence of transition data in Markov processes requires that the transition probabilities do not depend on the current state of the system (Woolhouse & Harmsen 1987a,b). That is, the system is zero order, or each row of **P** is identical. Stationarity and linearity of transition data require that all the transition probabilities are constant through time (Anderson & Goodman 1957; Goodman 1958, 1961; Billingsley 1961). Markovity of transition data requires that the transition probabilities depend on, and only on, the current state of the system. That is all transition probabilities are first order. The test for Markovity of transition data requires that the transition data be at least first order. One can ascertain this by testing for independence. Woolhouse and Harmsen (1987a, p.173) observed that most transition data are not independent in nature. These tests for Markovity can generally be extended to higher order behaviour (Woolhouse & Harmsen 1987b).

The methods or formulae used to test for independence; stationarity, linearity and Markovity are generally based on methods suggested by Anderson and Goodman (1957). These methods have been used extensively in the literature (Goodman 1958, 1961; Woolhouse & Harmsen 1987a,b; Caswell 1989; Sampson 1990). The theoretical premises of these tests generally require that all transition probabilities be non-zero. However, transition probabilities equal to zero are common in practice. In cases where zero transition probabilities are encountered, it is common practice to ignore transition probabilities of zero values (Woolhouse & Harmsen 1987b).

Testing for Order and Limiting Probabilities

In this section, interest is focussed on setting up the hypotheses that (i) the transition probabilities are of first order (against the alternative hypothesis that the transition probabilities are of a different order), and, (ii) the Markov chain has constant limiting transition probabilities. The first order Markov chain implies that the probability of the fisher's ground choice at one time interval depends only on the intention at the most immediate preceding time interval. In testing the hypothesis of time dependence of fleet transitions it is necessary to establish whether the observed transition probabilities, p_{ij}, could have come from a Markov chain with a given transition probability matrix.

The procedure for hypothesis testing is set up as follows. Let the null hypothesis for such a test be H_0: $\mathbf{P}=\mathbf{P}^0$, where $\mathbf{P}^0$ is a specific transition probability matrix. Consider p_0 (t) and p_1(t) the unconditional probabilities of finding the fishing process in state 0 and state 1 respectively, after t time periods. The probability distributions of the fishers' initial states, for state 0 and state 1 are given, therefore, as p_0 (0) and p_1 (0) respectively. For large n, the transition probabilities are related asymptotically to the normal distribution (Whittle 1955; Anderson & Goodman 1957; Parzen 1962; Bhat

1972; Ross 1980, 1983; Tierney 1994) as follows

$$\sum_{j=0}^{m-1} \frac{n_i(\hat{p}_{ij} - p^0_{ij})^2}{p^0_{ij}} \tag{23}$$

$$n_i^{\frac{1}{2}}(\hat{p}_{ij} - p_{ij}) \sim N[0, p_{ij}(1 - p_{ij})] \tag{24}$$

A test statistic identical to the goodness of fit statistic can be used (Anderson & Goodman 1957; Goodman 1958, 1961; Kelton & Kelton 1984). The test statistic has a χ^2 distribution with m-1 degrees of freedom, asymptotically (Bhat 1972). It is assumed that all p^0_{ij} are non-zero (Anderson & Goodman 1957; Woolhouse & Harmsen 1987b). If there are some zero elements in the i^{th} row, only the non-zero elements should be considered and the degrees of freedom should be adjusted (decreased) by the number of zero elements (Anderson & Goodman 1957). For problems in which the **P** matrix contains elements that are zero, the test statistic can be expressed in the form,

$$\sum_{i=0}^{m-1}\sum_{j=0}^{m-1} \frac{n_i(\hat{p}_{ij} - p^0_{ij})^2}{p^0_{ij}} \tag{25}$$

This test statistic has a χ^2 distribution with m(m-1)-d degrees of freedom asymptotically, where d is the number of zeros in $\mathbf{P}^0$. The summations shown above are taken, therefore, only over the states for which $\mathbf{P}_{ij}{}^0$ is greater than zero (Anderson 1954; Bhat 1972). The likelihood ratio criterion for the null hypothesis H_0: $\mathbf{P} = \mathbf{P}^0$ can be obtained from

$$\Lambda = \frac{f(p^0_{ij})}{f(\hat{p}_{ij})} \tag{26}$$

where, $f(\hat{p}_{ij})$ is the maximised value of the likelihood function (Bhat 1972). When the null hypothesis is true, -2 ln Λ has a χ^2 distribution with m(m-1) degrees of freedom and

$$2\ln\Lambda = 2[L(\hat{p}_{ij}) - L(P^0_{ij})] = 2\sum_{i=0}^{m1}\sum_{j=0}^{m1} n_{ij}\ln\frac{n_{ij}}{n_i P^0_{ij}} \quad (27)$$

The null hypothesis relates to a test for the time-independence of transition probabilities. Alternatively, the null hypothesis can be tested under the assumption of time-dependent Markov transition probabilities. This alternative test is important in that it is also a test for stationarity (Chung 1960).

Testing for Stationarity

To test for stationarity of the transition probability matrix, consider the one-step transition probability of a time-dependent process, $\mathbf{P}_{ij}(t)$. The test of the null hypothesis H_0: $\mathbf{P}_{ij}(t) = \mathbf{P}_{ij}$, for all t such that (t=1,2,..., T), is based on a maximum likelihood function given by $f(\hat{p}_{ij})$ and a likelihood ratio criterion Λ is given by

$$\Lambda = \frac{f\left(\hat{p}_{ij}(t)\right)}{f\left(p_{ij}\right)} \quad (28)$$

Since the number of transitions from fishing ground i to fishing ground j, $n_{ij}(t)$, during the transition period t, for t = 1,2, ..., T, are related to past transition counts, and the likelihood estimates of $P_{ij}(t)$ can be obtained using the expression

$$\hat{p}_{ij}(t) = \frac{n_{ij}(t)}{n_i(t)} = \frac{n_{ij}(t)}{\sum n_{ij}(t)} \quad (29)$$

Under the null hypothesis, -2 ln Λ has a χ^2 distribution with (T-1)(m(m-1)) degrees of freedom (Chung 1960; Goodman 1961; Bhat 1972, p.100; Kelton & Kelton 1984).

4.5.3 Characteristics of Transition Probability Matrices

Recall that in Section 4.5.1 it is argued that transition probabilities during t fishing periods can be represented by a matrix **P**, and that a matrix **A** is constructed by combining all intermediate transition matrices **P**. In comparing and contrasting transitions in two fishing seasons the overall transition matrix **A** is used since it represents a general description of fleet dynamics in the selected fishery for the selected fishing season. In the case of the NPF where daily and annual transition data are used, **P** and **A** represent daily and annual fleet transition probabilities respectively. In addition, matrix A(t) represents a time-dependent overall transition matrix. So, if any two annual transition matrices are similar or related, the information from past fishing periods that is imbedded in the matrix A(t) can be used to forecast transitions in the subsequent fishing period and to generate a forecast annual transition matrix A(t+1). It is necessary, therefore, to establish whether the series of transition matrices generated in one fishing season are similar to those generated in another fishing season. In addition to a check for similarity it is important to establish whether the transition matrices observed for the various fishing seasons can be generalised using a known stochastic process, or a set of stochastic matrices. It is argued throughout the thesis that where similarities and dissimilarities are evaluated using stochastic matrices, then the stochastic matrices are treated as if they have characteristics similar to those derived for real and complex matrices. Since the elements of the nonnegative matrices are the actual historical transitions (where no explicit modelling of transition probabilities has been attempted) it is noteworthy that transition probability matrices consist of time-dependent or time-independent elements. Recall that time-independence does not necessarily imply constant values, therefore time-independent transition probabilities may be a function of a set of other variables. However, the set of such variables that affect the transition probabilities is not considered in this section. A framework for including such endogeniety is presented in Section 4.6.

The emphasis on the similarity of transition matrices across fishing seasons presented in this section is consistent with the literature on stochastic matrices (Bharucha-Reid 1960; Prabhu 1965; Feller 1968; Romanovsky 1970). A Markov matrix is considered a stochastic matrix with positive eigenvalue, λ, where $0 < \lambda = \max \{\min p_{ij}\}$. That is, a Markov matrix is a stochastic matrix with at least one column entirely positive. Whittle (1955, p.237), for example, notes that Bartlett (1950) has shown that if P has no eigenvalues on the unit circle except the single value $\lambda=1$, then the number of observed direct transitions from i to j, n_{ij} are asymptotically normally distributed.

Whittle (1955) also shows that the spectral representation of the transition probability matrices is based on the eigenvalues, and includes eigenvalues in a system of equations used to derive some distributions and moments for Markov chains. It is clear from Whittle (1955) and Caswell (1989) that characteristics of transition probability matrices play a significant role in movement dynamics. To be consistent with the premise set by these authors, the importance of describing and evaluating the characteristics of the transition probability matrices used to represent fleet dynamics and the use of the characteristics to infer similarity or dissimilarity is therefore emphasised in this thesis.

The following selected characteristics of transition matrices are therefore computed in Chapter 5:

- eigenvalues and eigenvectors,
- tests of definiteness,
- orthogonality tests,
- norms, and determinants, singular values, and
- characteristic and minimum polynomials.

4.5.4 Similarity of Transition Probabilities and Destination Vectors

It is suggested in Section 4.5.3 that one method of checking for similarity between transition matrices involves the use of special characteristics of non-negative matrices. It is noteworthy, however, that inferring similarity/dissimilarity by finding special characteristics of non-negative matrices is a mathematical method and not a statistical method. An alternative method of testing for similarity that is based on statistical Markov chain theory is the method of checking for goodness-of-fit. The simple chi-square goodness-of-fit test is performed to test for similarity between transition probability matrices. In addition to the use of simple goodness-of-fit tests, statistical hypothesis can be tested using traditional measures of central tendency, dispersion, shape and peakedness of distributions. For example, hypothesis testing of difference in means and standard deviations of transition probabilities for different fishing periods can be conducted.

Tests for similarity can also be conducted for destination vectors. Tests for similarity based on destination vectors show whether two or more stochastic matrices possess similar properties since destination vectors show the proportion of vessels in the respective fishing grounds at the end of a fishing day. If transition matrices have similar characteristics suggesting similarity in the incidence of nominal fishing effort, then the transition data from which the matrices are constructed are more likely to come from the same distribution as the process used to model fisheries fleet dynamics. In addition, the tests for similarity can be used to test for changes in fleet dynamics projections based on simulating policy decisions and determining the likely impact of fisheries policy on future fishing patterns. The tests of similarity that are used to compare forecasts derived from simulation experiments are presented in Chapter 6.

4.6 Explaining Transition Probabilities

Markov chains form a simple class of stochastic processes. These provide the theoretical basis for a modelling framework for describing a fishing system (or fleet movement system) that can be in various states, among a fixed set of possible states. The fishing system jumps at unit time intervals from one state to another according to a probabilistic law. If the fleet movement system is in the ith state at time t, the next transition to the jth state occurs with a probability $p_{ij}(t)$. For each fisher, the set of transition probabilities $p_{ij}(t)$ or p_{ij} is prescribed for all fishing grounds and determines the behaviour of the system once its initial conditions are known. The future evolution of the process is determined, therefore, once the immediate past is known.

The elements of either a time-variant or time-invariant Markov transition probability matrix can be explained using a range of methods or models (Lee, Judge & Zellner 1970; McRae 1977; Aalen & Johansen 1978; Thornburn 1983; Woolhouse & Harmsen 1987a,b; Andersen, Hansen & Keiding 1991). In this thesis the MNL and the SUR are selected. For the purpose of illustrating either the MNL or SUR, and the use of time-varying and time-invariant transition probabilities in this thesis, the MNL is used to explain time-invariant transition probabilities and the SUR is used to explain the time-varying transition probabilities. This is a considerable improvement in modelling using a Markov framework since in general practitioners using the Markov framework treat transition probabilities as exogenous. This practice fails to recognise that historical transition probabilities are themselves a reflection of economic behaviour and decision making. In this thesis, we depart from the standard Markov modelling by recognising the endogeneity of transition probabilities, and by explicitly modelling the transition probabilities.

The Markovian framework used in this thesis presupposes that the fishers' decision making process regarding participating in the fishery, fishing in particular grounds, and participating in exploratory activity is motivated by the desire to achieve a set of economic objectives. Demand and stock uncertainty affect the dynamics of production regardless of the cost of harvesting. In addition to serving the expected profit maximisation objective, search is therefore a means of reducing uncertainty (Mason 1985; Pindyck 1995) about the biomass available for harvesting commercially. Uncertainty about the biomass distribution is likely to have an effect on the search patterns of fishers if they are sensitive to risk and uncertainty. The fisher is considered to adjust the level of search activity in order to maximise expected returns, subject to biological, technical and related constraints such as uncertainty and individual risk-taking behaviour.

Fishers' expectation of catch also influences their relocation decision. Each fisher exploits information available on fishing conditions, spatial abundance and competition, without making systematic errors. It is assumed that rational learning (Suppess & Atkinson 1960; Surton & Barto 1998) in fisheries search and harvesting is possible[5]. The fisher can be modelled as a rational learner or expert, and each skipper is assumed to believe that their relocations will converge to the true or most ideal relocation, given the circumstances of each fishing firm. Fishers are expected to change their search patterns and/or tactics when they expect a management policy change, within the constraints of competition in production and the fishing time.

[5] It is often argued that game theory presents learning issues similar to issues of expectation formation in economies with a sequence of incomplete markets and/or markets with traders that have different levels of information.

The direct result of rational learning may be difficult to show empirically, however. For example, in a Markovian model with rewards (Howard 1960, 1971a, 1971b; Bolton & Chapman 1986; Hastings 1989), it is often difficult to model the effect of net reward and the fishing path (relocation transitions) separately. Nonetheless, the transitions that the fisher makes may be considered a proxy for (i) the result of rational learning in fishing or (ii) the fisher's optimal use of the information available at the time.

4.6.1 Explaining Time-Invariant Fishers' Transitions Using the MNL Model

In this section a MNL model is used to explain the explicit choice probabilities of individual fishers. That is, the MNL model is used to explore what factors determine the transition probabilities. The MNL model is used widely in economics to predict the choices of rational economic agents (Luce 1959; McFadden 1974, 1981; de Palma & LeFevre 1981; Madalla 1983; Lioukas 1984; Stynes & Peterson 1984; Sellar, Chavas & Stoll 1986; Cameron 1988; Hagg 1989; Adamowicz, Jennings & Coyne 1990; Greene 1990, 1993; Train 1998; Campbell & Hand 1999; Holland & Sutinen 1999). Incorporating the MNL model into the basic Markov structure enriches, therefore, the general Markov structure.

Consider an individual fisher who has to choose a fishing ground among a set M of mutually exclusive fishing grounds. Each fishing ground has attributes that influence the fisher's choice. These perceived attributes (notably catch rates and stock abundance), and the economic rule used (fishing up to a point where expected marginal costs equals expected marginal benefit), guide the fisher's revealed preferences. For each fisher the attributes of each fishing ground can be denoted as Z, and the fisher's revealed preferences denoted as S. It is assumed that the main attribute S of each fishing ground is the expectation of catch and the catch rate history of the selected fishing ground, although uncertainty must be accounted for. However, given that a non-fishing state is also part of the choice set, the individual preference function is also interpreted as capturing the perceived opportunity cost of not fishing.

Each fisher is assumed to measure the desirability of each alternative fishing ground by a utility function U_j. For each fisher this utility function can be expressed as the sum of two components $V_j(Z_j,S)$ and $\mu\varepsilon_j$ (Hagg 1989). The term $V_j(Z_j,S)$ is non-stochastic and contains all the attributes of the fishing grounds. Note that it is assumed that Z_j is influenced, predominantly, by expected catch rate and the catch history of the selected fishing ground.

The stochastic part of this model, $\mu\varepsilon_{j,}$ is made up of two components. These are the error structure $\varepsilon_{j,}$ representing the effect of all unobserved variables, and a coefficient μ that represents a positive coupling constant that measures the importance of the error term. This stochastic component represents the capacity of the model to account for uncertainty. In equation form the utility function is

$$U_j = V_J(Z_J, S) + \mu\ \varepsilon_j \tag{30}$$

This equation can be modified to include fishery policy variables $F_J(F_{1j}, F_{2j})$ and fishing information (news) generally available to most fishers $I_J(I_{1j}, I_{2j})$. The model can therefore be expressed as

$$U_j = V_j(Z_J, S) + F_j(F_{1j}, F_{2J}) + I_j(I_{1j}, I_{2J}) + \mu\ \varepsilon_j \text{ for all } j = 1,2, ..., J. \tag{31}$$

It is then assumed that the fisher chooses the fishing state m if this choice will maximise the fishers expected utility. Therefore, the probability that a fisher facing a utility function U_j relocates from ground i and to ground j is given by p_{ij}. The probability p_{ij} can be written as,

$$p_{ij} = \frac{e^{\frac{v_J^k}{\mu^k}}}{\sum_{i=1}^{J} e^{\frac{v_i^k}{\mu^k}}} \tag{32}$$

This suggests that the expected utility derived from attributes of ground j is higher than that derived from attributes of ground i. Therefore, for a group of fishers, each fisher must select a fishing ground m out of a set of m fishing grounds. Sequential ground choices result in decision configurations, $m=\{m_1,m_2, ...,m_J\}$, and the number of fishers choosing a given configuration is n_j. In a unit time step process, n_j

represents fishers targeting a selected fishing ground[6].

It is assumed that the likely changes in the decision configuration are caused by differences in dynamic utilities, $u_j(m,t)$ that are state (space)-dependent and time-dependent. These utilities measure the fisher's perception of the desirability of each fishing ground. For each fisher the transition probabilities $p_{ij}(m,t)$ is also potentially both time- and state-dependent. In the case of time-invariant and state (space)-dependent transition configurations, then the transition rates take the following form (Smith 1981; Hagg 1989):

$$p_{ij} = v\, e^{u_j(m) - u_i(m)} \tag{33}$$

where v is a flexibility parameter. The total transition rate is then given by

$$w_{ij} = n_i\, p_{ij}(m) = n_i\, v\, e^{[u_j(m) - u_i(m)]} \tag{34}$$

The time-dependent equivalent expression is

$$p_{ij} = v\, e^{u_j(m,t) - u_i(m,t)} \tag{35}$$

and, the total transition rates related to time- and space-dependent transitions is

$$w_{ij} = n_i\, p_{ij}(m,t) = n_i\, v\, e^{[u_j(m,t) - u_i(m,t)]} \tag{36}$$

Since each fisher must choose a set of fishing grounds, the change in the decision configuration over time can be shown as

$$\frac{dp(m,t)}{dt} = \Sigma\, w_{ji}(m^{ij})p(m^{ij},t) - \Sigma\, w_{ij}(m)p(m,t) \tag{37}$$

where, p(m,t) is the probability of finding a certain decision configuration realised

[6] Note that the variable n_j is used as a dependent variable in SUR modelling.

at time t. This equation captures stochastic and dynamic components of the decision process (Hagg 1989).

The most probable stationary decision configuration is $\hat{n} = \{\hat{n}_1, \hat{n}_2, ..., \hat{n}_j\}$, where $\hat{n}$ represents the most probable number of individuals who have chosen fishing ground j. Given that the population of fishers is N, it can be argued that $p_j = \frac{\hat{n}_j}{N}$, which is equivalent to the probability that a fisher selects alternative m[7]. Since the non-fishing state is included in the set of alternatives, fishers select from J+1 available alternatives.

Given this type of choice problem, the probability that a fisher selects alternative m from m fishing states is

$$P_{t0} = \frac{e^{X_t \beta_j}}{\left[1 + \sum_{j=1}^{J} e^{X_t \beta_j}\right]} \tag{38}$$

where, X_t represents decision variables that are functions of attributes of fishing states and β_j represents the unknown parameters that are common to all fishers. For each fisher the choice of relocating from one fishing ground to another is represented by a binary variable y_{ij} that takes the value of 1 if the alternative j is chosen and a value of zero otherwise (Judge et al. 1985, 1988; Greene 1990, 1993; Griffiths, Hill & Judge 1993). The log density for each fisher can be shown, therefore, as follows (SHAZAM 1993, 1997):

$$L_t = \sum_{j=1}^{J} y_{tj}\left(X'_t\, \beta_j\right) - \log\left[1 + \sum_{j=1}^{J} e^{X'\, \beta_j}\right] \tag{39}$$

Given the assumption of independence, the log-likelihood function is obtained by summing individual log-densities.[8]

[7] Note that the number of fishers remains the same for each fishing season since the non-fishing state is included as one of the alternatives.

[8] Each observation is assumed to be drawn from independent, but not identical, multinomial distributions.

Since $y_{ij}=1$ represents the fisher's choice of moving from ground i to j (otherwise $y_{ij}=0$), then using p_{ij} for the probability that $y_{ij}=1$, the sum of the probabilities can be expressed as

$$p_{i1}+p_{i2}+p_{i3}+\ldots+p_{ij}=1, \text{ that is } \sum_{j=1}^{J} p_{ij}=1 \tag{40}$$

The MNL model is expressed by combining

$$\log\left(\frac{p_{i2}}{p_{i1}}\right)=\beta_2 X_i;\ \log\left(\frac{p_{i3}}{p_{i2}}\right)=\beta_3 X_i, \tag{41}$$

then estimating the parameters of the MNL model for J fishing states by using

$$p_{ij}=\frac{e^{\beta_j X_i}}{1+\sum_{j\neq i}^{J} e^{\beta_j X_i}} \tag{42}$$

and defining the log likelihood function, which will be maximised, as

$$\log L = \sum_{i=1}^{n}\sum_{j=1}^{J} y_{ij} \log p_{ij} \tag{43}$$

The MNL model represents, therefore, decision making where the fisher is motivated by maximising expected utility derived from selecting and making a transition from fishing ground i to fishing ground j. This level of utility depends on a set of variables representing the attributes of the chosen fishing ground, as well as attributes of each fisher, as well as a random disturbance term[9]. The random disturbance is included to reflect uncertainty in the system, including intrinsically random choice behaviour, and measurement and/or specification error. In particular it may reflect unobserved random attributes of the different fishing states, including those related to fish stock size and spatial temporal distribution.

If there is a mean-variance trade-off implicit in the utility function, then fishers will worry about reducing uncertainty in searching and harvesting. It is noteworthy that in the MNL model, the odds of a particular choice are unaffected by the presence of

[9] It is assumed that disturbances are independently and identically distributed with the Weibull density functions.

additional alternatives; a property called the "independence of irrelevant alternatives".

In addition, none of the variables represented in X_{ij} can be constant across all alternatives since this would imply that the associated parameter would not be identified. For example, many particular fishery attributes, such as length of boat used, type of gear used, experience of skipper, are constant across fishing grounds. Similarly, gear characteristics are not included in the estimating equations because they are not altered considerably across fishing grounds or during a particular season or fishing period. Variables that would provide information about the choices made include the average CPUE in the selected fishing ground and the level of participation in a fishery, among other variables. These factors vary across alternatives for each individual.

Judge *et al.* (1985, p.771) proposed a model specification that allows explanatory variables to have differential effects or impacts upon the odds of choosing one alternative over another[10]. The appropriate likelihood function is obtained by substituting the relevant p_{ij} in the likelihood function.[11]

The odds when J alternatives are available are given by

$$\frac{p_{i1}}{p_{i2}} = \frac{e^{X_{i1}\beta}}{e^{X_{i2}\beta}} \tag{44}$$

The selection probabilities are then given by

[10] The odds of choosing fishing ground 1 instead of fishing ground 2 where J alternatives are available is given by $\frac{p_{i1}}{p_{i2}} = \frac{e^{x_{i1}'\beta}}{\sum_{j=1}^{J} e^{x_{ij}'\beta}} \Bigg/ \frac{e^{x_{i2}'\beta}}{\sum_{j=1}^{J} e^{x_{ij}'\beta}}$.

[11] The appropriate likelihood function is obtained by substituting $\hat{p}_{ij}$ in the likelihood function $L = \prod_{i=1}^{T} p_{i1}^{y_{i1}} p_{i2}^{y_{i2}} p_{i3}^{y_{ij}}$ (Judge et al. 1985, p.772).

$$p_{ij} = \frac{e^{x_{ij}\beta_j}}{\sum_{j=1}^{J} e^{x_{ij}\beta_j}} \tag{45}$$

where the parameter vector is indexed by j[12]. These probabilities can then be used in the matrix of transition probabilities for the Markov model of fleet dynamics.

4.6.2 Explaining Fishers' Time-Varying Transitions Using SUR

For a Markov chain, the past and future are conditionally independent given the present. This Markov property implies that future probability behaviour of the process in question is determined once the state of the system at the present stage is known[13]. The Markov property imposes a restriction that is highly convenient mathematically (Bailey 1964). A large number of real situations can be studied usefully, at least as a first approximation, by means of a suitably-chosen Markov process or chain. However, transition probabilities are generally time-dependent and thus impose a time-varying Markov structure (Bacchus, Boutlier & Grove 1996, 1997). Despite this, it is customary to employ derivative techniques for extracting time-invariant Markov process from time-varying Markov processes.[14]

Fleet movements in the search for and harvesting of prawns in Australia's NPF are characterised as finite, discrete stochastic processes. The time-varying Markov model requires that,

$$W(t+1) = W(t)P \tag{46}$$

where, P is a transition probability matrix representing the stochastic movement of fleet to alternative fishing grounds, and W(t) and W(t+1) are state probability vectors at time period t and t+1 respectively. It is obvious that, in the case of movement

[12] The indexing indicates the differential impacts explanatory variables may have on the alternative fishing states chosen.

[13] A symmetrical extension of the Markov property suggests that the Markov property still holds in reversed time. This property is referred to as the time reversibility of the Markov property.

[14] The techniques include (i) searching for embedded Markov chains, (ii) including supplementary variables, or (iii) using the augmentation technique. The transition probabilities of the extracted chain (the supposedly embedded Markov chain) are then tested for Markovity, homogeneity, stationarity, regularity and order.

between fishing grounds, W(t+1) is the destination (incidence) vector and W(t) is the origin or starting vector. It is assumed that the transition process is first order, linear, stationary and ergodic. Transition data tend, however, to show non-stationarity and non-linearity (Woolhouse & Harmsen 1987b), and a bioeconomic process, such as fishing, is non-homogeneous over space and time.

In developing a time-varying Markov representation of the fishing process it is important to consider the following.

- First, the time interval over which the transition probabilities are estimated must be short enough to allow a maximum of one transition between states, per vessel, per unit time.
- Second, the number of states can be constant over the entire period of analysis or may vary across defined time periods. The configuration of the state space may also be variable or constant.
- Third, a range of economic and non-economic factors that condition fleet movements, affect the transition probabilities.

The development of an appropriate transition matrix model requires, therefore, the identification of factors that cause P to change over time. These processes include economic processes (congestion, competitive behaviour, production efficiency, transfer of information about fishing conditions and outcomes), biological processes (stock recruitment, natural mortality), technical processes (sweep width, gear selectivity, the GPS factor), management processes (catch restrictions, seasonal closures), and other related processes, such as lunar periodicity.

For example, for fishers searching in the NPF, the likelihood of any vessel relocating to a nominated ground depends on factors such as expectation of catch, previous catch, congestion and/or productivity history of targeted fishing grounds, or seasonality in the productivity of different fishing grounds.

A Markov chain that shows the time-varying nature of the transition process for a group of fishers leaving state i and entering state j can be given in the form,

$$W(t+1) = W(t)\,P(t) \tag{47}$$

where, P(t) is a matrix of estimated transition probabilities. For example, the transition probabilities can be represented in the form,

$$P_{ij}(t) = p[CPUE^{e}_{j}, CPUE_{i}, n_{j}(t), n_{j}(t+1), \mathbf{X}_{j}(t), D(t), \varepsilon] \tag{48}$$

where, $P_{ij}(t)$ is the estimated transition probability; $CPUE^{e}$ is expected CPUE in the targeted fishing ground[15]; $CPUE_i$ is the actual CPUE in the current fishing ground (that is, the fishing ground of origin); n_j, is the number of vessels in fishing ground j; D is a dummy variable for lunar periodicity; $X_j(t)$ is a matrix of variables representing attributes of the fishing state and the fisher, and ε is a random error term. The equation used for obtaining estimated transition probabilities can be complex (Woolhouse & Harmsen 1987a,b). In most general cases the time-dependent transition probability function is used and this is specified as

$$W(t+1) = W(t)\,p_{ij}(t) \tag{49}$$

where $p_{ij}(t)$ is specified in equation [48]. The specifications in equations [48] and [49] are estimated in stages; initially as individual regression equations. A multivariate systems approach is employed in the subsequent stages since the equations are functions of variables that depend on events in other spatial structure. More specifically, a reliable estimate of the temporal series of transition probabilities cannot be estimated independently of the temporal series of transition probabilities. An estimate of the family of transition probabilities using (i) SUR (ii) the Error Component Method (ECM) (Anselin 1988) or (iii) the multinomial estimation is preferred.[16] Estimation of time-dependent Markov transition probabilities uses daily and weekly transition probabilities.

[15] This variable may be proxied by the searchers' average catches in that fishing ground in the previous fishing season.

[16] The multinomial estimation of time varying transition probabilities is detailed in McRae (1977). The theory of SUR and ECM estimation is detailed in Anselin (1988). Econometric estimation of SUR models is detailed in Judge et al. (1985, 1988) and Greene (1993, 1990).

Having identified a range of factors that may affect the transition probability matrix, the general form for a time varying model, therefore, (i) captures the temporal and spatial variation in fleet dynamics; (ii) provides a sequence of projection matrices, (iii) provides a sequence of stage-structured destination vectors, **P**(t), generated by the sequence of projection matrices operating on an initial population vector.

In the case of the NPF, reliable data are not available to support explicit modelling of a time varying Markov probability matrix as suggested in equations [45] and [46] above. It is reasonable to propose, therefore, the use of selected variables and generate estimates of transition probabilities based on a stochastic process that account for contemporaneous correlation in the error structure. The SUR model can be used to accomplish that. It is useful, therefore, to estimate transition probabilities using SUR since the Markov chain specifies the probability distribution of the states at the next time period as a function of the environment at the current time period. If that probability distribution does not change over time, the environment is said to be homogeneous. If the distribution changes over time, the environment is said to be inhomogeneous. The pattern of autocorrelation, or lack thereof, in a stochastic environment can have a major impact on local exploitable biomass.

It is of interest to consider simulating the time-variant transition probabilities using variables that are specific to the fishery. The justification for this approach can be developed as follows. One can argue that the daily transition matrices are different, and therefore cannot be used as a generalisation of the fishing process over the entire fishing period. Caswell (1989, p.209) argues that no study has obtained enough environmental information to specify even a simple model, so the neglect of more complex environmental models is no great loss.

Therefore, as a generalisation, one may capture a tremendous range of complex dynamic behaviours in a Markov framework using simpler model specifications of time-varying transitions. The simpler specification adopted in this thesis is that relocations depend on relative catches and the number of vessels in different fishing grounds. These key variables and the contemporaneous error structure accord spatial dependence and heterogeneity. A space-time SUR model that draws extensively on the study of spatial econometrics developed by Anselin (1988) is therefore used. The importance of spatial econometrics lies in incorporating (i) the role of spatial interdependence (Griffith 1981, 1987), (ii) the asymmetry in spatial relations (Griffith & MacKinnon 1981), (iii) the importance of space-specific explanatory factors, (iv) differentiation between ex-post and ex-ante interaction (Fotheringham & O'Kelly 1989), and (v) explicit modelling of space (Anderberg 1973; Bennett 1979; Paelinck & Klaassen 1979; Cliff & Ord 1981; Anselin 1984, 1988; Ordland 1988). In this space-time SUR model spatial heterogeneity can be illustrated as follows:

$$Y_{it} = f_{it}(X_{it}, \beta_{it}, \varepsilon_{it}) \tag{50}$$

where i is the spatial unit (fishing ground), t is the time period, f_{it} is a time-space specific functional relationship which explains the value of the dependent variable, $\mathbf{Y}_{it}$ (or a vector of dependent variables) in terms of a vector of independent variables $\mathbf{X}_{it}$, a vector of parameters β_{it}, and an error term ε_{it} [17].

The temporal dimension introduces the complexity of spatial econometric models. The modelling takes into account patterns of cross-sectional dependence, space-time dependencies and heterogeneity[18], and presents coefficients that vary across space or time when the error terms are correlated contemporaneously (Anselin 1988; Haining 1994).

In the case of the NPF, the dependent variable $\mathbf{Y}_{it}$ used in the space-time SUR as expressed in equation [50] represents the number of fishers in fishing ground i at the end of fishing time period t. In the most familiar SUR design, the regression coefficients β_i vary by spatial unit, but are constant over time. The error terms are spatially (contemporaneously) correlated. That is, there is a constant covariance between errors for different spatial units at some point in time. It is noteworthy that equation [49] is specified for each fishing ground. One of the equations is omitted

[17] A test of spatial residual autocorrelation in SUR models is developed by Anselin (1988, p.138).
[18] The structure to encompass a number of possible space-time dependencies and patterns of spatial heterogeneity. These can include forms such as constant variance, spatial heterogeneity, time -wise heterogeneity, space-time specific variance, contemporaneous spatial correlation, time-wise correlation, and space-time correlation.

in the estimation. Therefore in an m-state Markov system, only m-1 equations will be estimated and the remaining equation will be recovered from the set of m-1 estimates of transition probabilities. In general the number of explanatory variables used in **X** can be different for each equation (spatial unit)[19]. The model for space-time SUR can be summarised as[20]:

$$\begin{aligned} Y_{it} &= X_{it}\beta_t + \varepsilon_{it} \\ E[\varepsilon_{it}, \varepsilon_{is}] &= \sigma\sigma_{ts} \\ E[\varepsilon_{it}, \varepsilon_{jt}] &= \sigma_{ij}(t) \\ E[\varepsilon_{it}, \varepsilon_{js}] &= \sigma_{ij}(t,s) \ \forall i \neq j, t \neq s \end{aligned} \tag{51}$$

Note that the space-time correlation (that is when the pattern of dependence reaches across space and over time simultaneously)[21], can be shown as

$$E[\varepsilon_{it}, \varepsilon_{js}] = \sigma_{ij}(t,s) \tag{52}$$

4.6.3 Using the SUR Specification to Explain Fleet Destinations

The argument for using time-varying Markov transition probabilities is based on the existence of a relationship between variables that fishery managers can observe and possibly control and transition probabilities. Data series on variables that are needed to estimate the transition vectors reliably are not generally available, however. In addition, the transitions also depend on each other. For example, if a large proportion of vessels is destined to a particular state, then that movement changes the proportion of vessels that are entering other states. This suggests that it is very likely that there is significant contemporaneous correlation in prediction errors. In order to take into account relationships between the determinants of the destination vectors and the relationship between vectors, destination vectors must be estimated using a technique that incorporates contemporaneous variation. In the SUR modelling approach destination probabilities are explained by average catch rates in the respective fishing grounds and related variables.

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[19] In the spatial SUR model, the regression coefficients are constant across space, but may vary for each time period, thus β_t. The error terms are temporally correlated, that is, there is a constant covariance between errors for different time periods for the same space spatial unit.

[20] In this spatial and temporal model the coefficients are variable across space and time.

[21] This occurs when both $i \neq j$ and $t \neq s$, hold.

Consider a series of destination probability vectors for the fleet in fishing periods 1991 through 1994. In addition, consider estimates of these destination vectors using catch variables. The explanatory variable used in this simple function is catch per boat on the previous day. One can argue that, *a priori,* the proportion of fishers moving into a fishing ground will be positively related to catch in that selected fishing ground on the previous day. The thrust of this type of analysis is similar to that employed by Campbell, Meyer and Nicholl (1993), except that they used an Almon polynomial for the independent variables. Although the advantages of specifying an Almon polynomial include the capability of computing the optimal lag length, the approach by Campbell, Meyer and Nicholl (1993) is not applied directly to the estimation of destination vectors for several reasons.

First, fitting the Almon polynomial is likely to introduce autocorrelation. Second, a longer polynomial might introduce the problem of multicollinearity. Third, a SUR model that does not specify a polynomial expression and simply uses the previous day catch is consistent with a first order Markov chain. Therefore using an Almon polynomial would suggest estimating a Markov chain of order higher than unity. Fourth, it is computationally convenient to constrain the SUR equations to the same lag length. The search for an optimal lag length for each of the destination vector equations complicates the proposed model. Finally, it is useful to introduce the issues relating to contemporaneous correlation in the error structure. This is important since the number of boats relocated to each fishing ground (represented by the destination vector) depend on the destination probabilities elsewhere. These interdependencies require individual regression equations that seem unrelated initially, to be actually related. The Markov model developed in this thesis, therefore, embodies the following properties: a first order Markov chain; contemporaneous correlation; and seemingly unrelated regression coefficients[22].

[22] Note that in a four-state fleet dynamics model, three out of four equations are estimated. This is convenient for estimating destination vectors since for each time period the destination probabilities sum to unity. Three destination probabilities are therefore estimated and the fourth is treated as residual.

4.7 Concluding Remarks

The Markov chain used in describing and explaining fleet movement in the NPF is a process in which there is a finite number of states or outcomes that can be occupied at any given time. The states used in the fleet dynamics problem are fishing grounds. These fishing grounds do not overlap and cover all possible outcomes. The Markov system allows coefficients of the system to vary in a probabilistic manner, and form part of a system of difference equations. In this Markov model the individual vessels may move from one fishing ground to another fishing ground at each time step, and there is a probability associated with this transition for each possible outcome. The Markov chain will be used to model an m-state fishing decision problem for the NPF fleet.

Fleet movement in the NPF is modelled as a process consisting of a sequence of events with the following properties. Fleet movement is an event that has a finite number of states. Fishing is always in one of these states, at each period or stage. At each stage or period of the process, a vessel can transit from its present state to any other state or remain in the same state. The probability of moving from one state to another in a single stage is represented by a transition probability matrix for the row elements lie between 0 and 1 and sums to unity.

In the generalised model, it is important to focus attention on incorporating the following: ground attractiveness; catch history and skippers' expectation of CPUE; lunar phase or cycle effect; and time-varying transition probabilities[23] as well as variables affected by fishery managers. It is assumed in this thesis that the fishing system and fleet dynamics are characterised by rational expectations. The system is modelled as if driven by what happened in the past, and what is likely to happen in the future based on past data and present data or general information about possible events. The model assumes that fishing firms have been operational for a considerable period of time and that the experience of the skippers and related information transfer processes enable one to characterise the process as stable.

[23] Note that any transition in the state-space reflects economic rationality in fishers' search behaviour.

The application of the Markov structure developed in this chapter to the NPF is reported in subsequent chapters. In Chapter 5 an example of a Markov fleet dynamics model of the NPF that is based on time-invariant transition probabilities is presented. The data requirements for this model are highlighted. The extension of the two-state model to an m-state Markov model of fleet dynamics is shown. Simulations of historical transitions are performed, and inferences drawn from the simulations.

Individual choice of fishing ground is modelled using an MNL model. The application of the MNL has been restricted to time-invariant transition matrices. A time-varying Markov structure is also presented. The time-varying Markov destination vectors in the NPF are explained using a SUR model. Management implications of fleet dynamics are simulated in Chapter 6. Recall that the pattern of vessel deployment during each fishing period is presented in the form of an annual transition matrix. So the annual transition matrices for the respective fishing periods are compared and contrasted using simple special characteristics of matrices such as eigenvalues. Matrices with similar special characteristics are deemed to have been developed or generated by a similar process, in this case, by the Markov process of fleet dynamics.

CHAPTER 5

TRANSITIONS AND ESTIMATES FROM MNL AND SUR MODELS

5.1 Introduction

The focus of Chapter 5 is on using the framework developed in Chapter 4 to describe and explain fleet dynamics in Australia's NPF. The numerical technique used to accomplish these objectives is a Markovian process and requires data on actual vessel movements throughout the fishing season, and on the initial distribution of vessels. In describing fleet movement, attention is focussed on a stationary, time-invariant (homogeneous) Markov process[1] and stationary observed transition probabilities. The transition probabilities are represented using transition probability matrices. Characteristics of these transition probability matrices are then evaluated. In addition, the results of an MNL model used to account for variations in vessel movements displayed by the time-invariant transition probabilities are reported. Note that the MNL can also be estimated using time-varying transition probabilities. Similarly, the SUR estimations can also be made for time-invariant transition probabilities. The results of estimating a SUR model to explain time-varying transition probabilities in the NPF are also presented[2].

In order to describe and explain vessel movements using the Markovian framework there is need to specify the states of the Markov system. In this chapter, the following state models are considered:

- three-state Markov model (to fish inside or outside the Gulf of Carpentaria, or not to fish),
- four-state Markov model (not to fish, and to fish inside the Gulf of Carpentaria, to fish elsewhere within the NPF, to fish outside the NPF), and
- six-state Markov model (not to fish, and to fish in five selected groups of statistical fishing zones (SFZs)).

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[1] This class of stochastic processes is discussed extensively by Parzen (1962), Bailey (1964), Bharucha-Reid (1962), Bartos (1967), Martin (1967), Bhat (1971), Howard (1960, 1971a, 1971b), Kemeny & Snell (1976), Iosifescu (1980), Ross (1980, 1983) and Karlin & Taylor (1975, 1982).
[2] This class of stochastic processes is discussed extensively by McRae (1977) and Lee, Judge and Zellner (1970).

Figures 5.1 to 5.3 show the states in the three, four and six state Markov models. While working at these levels may be of practical value, fishery managers may also want to consider the following Markov models:

- two-state Markov model (to fish or not to fish)
- twelve-state Markov model (fishing in all NPF's SFZs and outside the NPF, as well as not fishing),
- sixteen-state Markov model (fishing in all SFZs, and not to fish)
- seventy three-state Markov model (fishing in all the seventy-two SFGs and not to fish.

Management practices and zoning for scientific research dictate which state model will be most relevant in any particular circumstance. For example, the use of SFZs in the NPF requires the use of fishing areas outside the NPF, the non-fishing state and ten SFZs in the NPF. Fishery independent research activities have focused mainly on smaller areas within the Gulf of Carpentaria (supporting the use of the three-state model). For sampling purposes, the SFZs are split into a total of seventy-two smaller SFGs. For management purposes focused on closing the entire fishery or shortening the length of the fishing season it is important to look at the decision to participate in the fishery. This requires, therefore, the use of a two-state model representing fishing or no fishing. Any of these state model specifications are referred to as m-state Markov fleet dynamics models, where m refers to the number of states. Each of these m-state Markov fleet dynamics models uses vectors to show the proportion of vessels targeting a selected fishing ground. These vectors, referred to throughout the thesis as destination vectors, can take four forms, namely: historical (or observed)[3], estimated[4], projected[5] or simulated[6] destination vectors.

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[3] Historical or observed destinations vectors are those obtained by computing the number of vessels in a particular fishing ground.

[4] Estimated destination vectors are endogenous and can be estimated using the MNL or SUR.

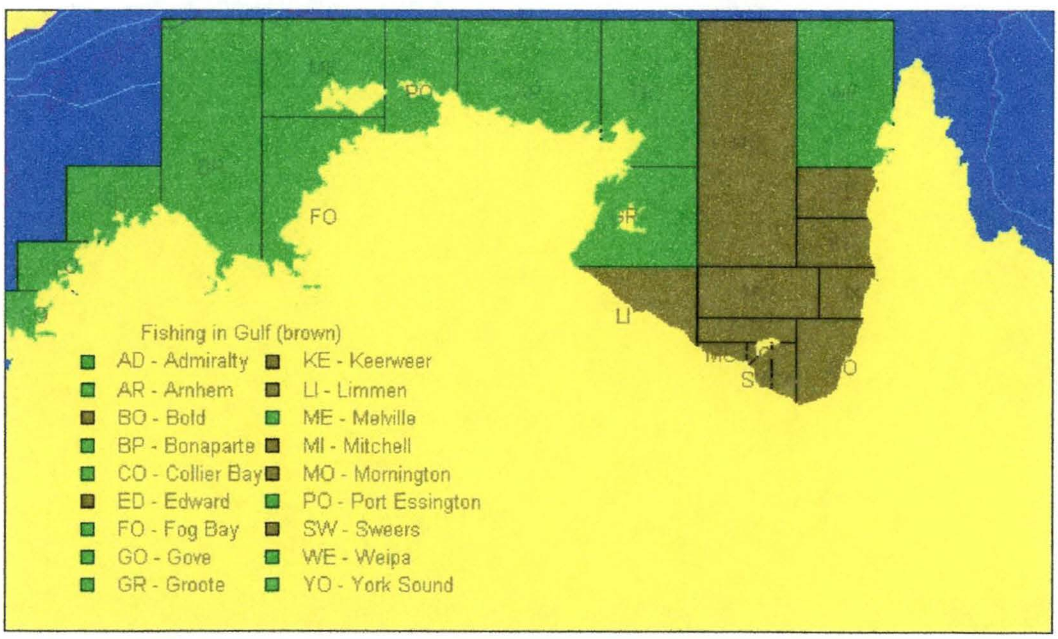
[5] Projected destination vectors are obtained from the product of an observed transition matrix and a known starting vector. The projection emphasises, here, the use of a Markov process.

[6] Simulated destination vectors are obtained from the product of a simulated transition matrix and a known or simulated starting vector.

The matrices describing fleet dynamics, and whose characteristics are evaluated, are based on a six-state Markov model[7]. Empirical estimates for the MNL and SUR models are based on the three-state Markov model.

Although only a subset of the results has been reported, the characteristics of matrices depicting two, three, four, six, twelve, sixteen and seventy-three state Markov fleet dynamics models specified above, have been made by the researcher, for all fishing periods. Emphasis is placed on evaluating, empirically, the three- and six-state models because the spatial and temporal resolution conferred by such model specifications has sufficient data points. The methods and techniques used to obtain the results reported in this chapter can be used consistently, however, over any m-state fleet dynamics model since within each model the general framework of fishers' effort allocation decisions is the same.

Figure 5.1 States in a Three-state Markov Fleet Dynamics Model of the NPF



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[7] In the six-state Markov model state 0 is the non fishing state; state 1 grounds are coded from 413 to 444; state 2 grounds are coded 451to 493, state 3 grounds coded 461 to 477; state 4 grounds are coded 481 to 517; state 5 grounds are coded 521 to 621.

Figure 5.2 States in a Four-state Markov Fleet dynamics Model of the NPF

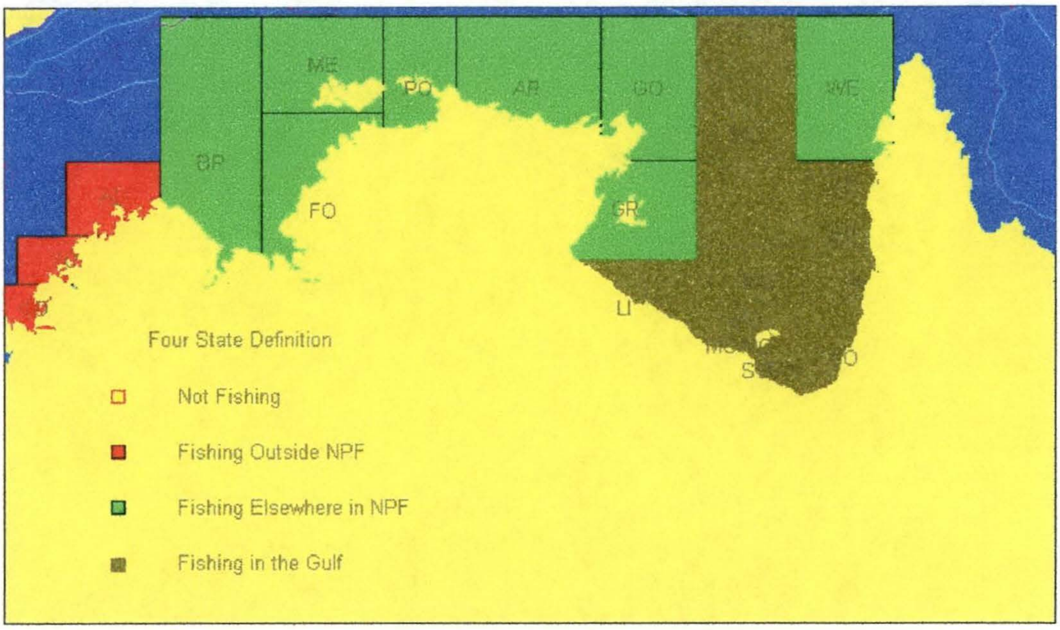
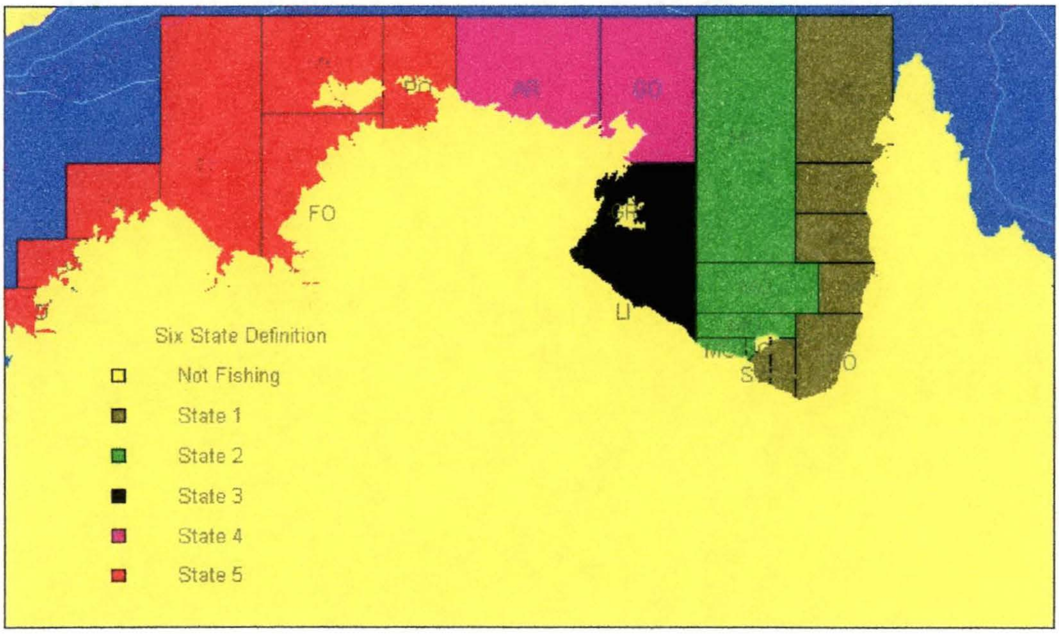


Figure 5.3 States in a Six-state Markov Fleet Dynamics Model of the NPF



Individual vessel data are used to obtain a spatial and temporal series of transition numbers and probabilities that may be used for describing and forecasting group behaviour[8]. Results reported in this chapter are based on confidential data on vessel movement and catch obtained from CSIRO. Four fishing seasons, namely 1991

[8] This is in contrast the method by Lee, Judge and Zellner (1970) and Bartholomew (1973).

through 1994, are considered. Forecasts are made for each of these fishing seasons in Chapter 6 and are used as a check on the reliability of the Markov model. The rest of this chapter is structured as follows. In Section 5.2 transition numbers and probabilities of the six-state fleet dynamics model are reported. Special characteristics of the transition matrices, namely eigenvalues, eigenvectors and other related characteristics are presented in Section 5.3. The selected characteristics are used to compare annual fishing patterns across years. This approach is unique in the analysis of fleet dynamics. In Section 5.4 transition matrices in past fishing periods are used to project likely vessel movements in subsequent fishing periods. Results of the similarity of Markov transitions across fishing periods are also presented. Estimates of the SUR model are reported in Section 5.5. Estimates of the MNL model are reported in Section 5.6. Concluding remarks are drawn in Section 5.7.

5.2 Transitions in a Six-state Markov Fleet Dynamics Model

Real and virtual transition numbers for 1991 through 1994 fishing periods are displayed in Tables 5.1 through 5.4 respectively. The transition numbers over the period 1991 to 1994 are summed and presented in Table 5.5 in the form of a transition number matrix. The transition numbers shown in Tables 5.1 through 5.4 are then converted into annual transition probabilities. These annual transition probabilities are displayed in Tables 5.6 through 5.9. The mean and standard deviation of these annual transition probabilities are given in Table 5.10. The transition matrix shown in Table 5.5 is converted to a matrix of average annual transition probabilities and displayed in Table 5.11. A chi-square goodness of fit test is used to compare the pattern of transitions for the fishing period 1991 to 1994, as shown in Tables 5.6 through 5.9. Similarly, the elements of transition probability matrix, shown in Table 5.10, are compared with the transition probability matrix shown in Table 5.11, using the chi-square statistic. Such comparisons are important in determining similarity or resemblance of transition probability matrices.

Table 5.1 Number of Real and Virtual Transitions in 1991 Fishing Period

	TO						
FROM	state 0	state 1	state 2	state 3	state 4	state 5	Row Totals
state 0	24 271	384	188	336	232	502	25913
state 1	478	4 511	264	41	100	0	5 394
state 2	111	221	2 423	258	267	0	3 280
state 3	416	23	158	7 949	302	0	8 848
state 4	232	99	247	264	2 541	113	3 496
state 5	565	0	0	0	54	3 878	4 497
Column Totals	26 073	5 238	3 280	8 848	3 496	4 493	51 428

The results in Tables 5.1 through 5.4 represent transitions between states. The structure of the transition matrices is as follows: rows represent the departing state and the columns represent the destination state. The elements of these matrices represent the number of transitions made from the departing state to the destination state during the relevant fishing period. The diagonal elements represent virtual transitions (remaining in the same state) whereas the off-diagonal elements indicate real transitions (instances where boats relocated from one fishing ground to another). The number of real transitions tends to be smaller than the number of virtual transitions. For example, in all fishing periods 1991 through 1994 no vessel relocated from state 5 to states 2. Similarly, there is no record of transitions from either state state 5 to either state 1 or 2 for the fishing period 1991 through 1994. Over the same period a very low number of vessels relocating from state 5 to state 3 or state 4 was recorded. One transition is recorded for the movement from state 3 to state 5 in the 1992 fishing season, and for the movement from state 1 to state 5 in the 1994 fishing. On the other hand, vessels made the virtual transitions from state 1 to state 1 a total of 4511 times in 1991, 4171 times in 1992, 2805 times in 1993 and 4135 times in 1994.

Table 5.2 Number of Real and Virtual Transitions in 1992 Fishing Period

	TO						
FROM	state 0	state 1	state 2	state 3	state 4	state 5	Row Totals
state 0	22 609	287	118	324	268	442	24 048
state 1	339	4 171	234	35	253	0	5 032
state 2	68	176	1 574	204	215	0	2 237
state 3	400	13	130	9 237	428	1	10 209
state 4	304	246	181	408	4 296	103	5 538
state 5	476	0	0	1	78	3 211	3 766
Column Totals	24 196	4 893	2 237	10 209	5 538	3 757	50 830

The column totals in Tables 5.1 through 5.4 represent the total transitions to a specified destination state during the relevant fishing period. In all four fishing periods, state 2 was least visited. Note that in comparing the transitions to each state, the non-fishing state (state 0) is excluded. This is done because the real transitions to state 0 include transitions due to season closure as well as choices made *not to fish* exercised during the fishing period. These destination values indicate that state 3 was the most visited state in each of the fishing periods. A total of 8 848, 10 209, 9 480 and 9 301 transitions originating from state 3 are recorded for each of the fishing periods. Note that since each transition between fishing states represents a deployment of nominal fishing effort, it follows that a high level of effort is directed to state 3.

Table 5.3 Number of Real and Virtual Transitions in 1993 Fishing Period

	TO						
FROM	state 0	state 1	state 2	state 3	state 4	state 5	Row Totals
state 0	14 515	197	102	215	216	397	15 642
state 1	231	2 805	172	41	111	0	3 360
state 2	61	105	1 264	244	174	0	1 848
state 3	309	18	147	8 647	359	0	9 480
state 4	215	115	163	333	3 143	85	4 054
state 5	435	0	0	0	51	3 103	3 589
Column Totals	15 766	3 240	1 848	9 480	4 054	3 585	37 973

Table 5.4 Number of Real and Virtual Transitions in 1994 Fishing Period

	TO						
FROM	**state 0**	**state 1**	**state 2**	**state 3**	**state 4**	**state 5**	**Row Totals**
state 0	13 606	164	77	211	185	331	14 574
state 1	230	4 135	107	24	181	1	4 678
state 2	51	106	1 504	94	199	0	1 954
state 3	213	4	82	8 616	386	0	9 301
state 4	258	156	184	356	3 554	54	4 562
state 5	339	0	0	0	57	2 508	2 904
Column Totals	14 697	4 565	1 954	9 301	4 562	2 894	37 973

The total transitions made in the period 1991 through 1994 are shown in Table 5.5. Over this period a total of 15 622 virtual transitions were made to state 1, 6 765 virtual transitions were made to state 2, 34 449 virtual transitions were made to state 3, 13 534 transitions were made to state 4 and 12 700 were made to state 5. The real transitions summed over all annual transition matrices are fewer than virtual transitions.

Table 5.5 Number of Real and Virtual Transitions in 1991-1994 Fishing Period

	TO						
FROM	**state 0**	**state 1**	**state 2**	**state 3**	**state 4**	**state 5**	**Row Totals**
state 0	75 001	1 032	485	1 086	901	1 672	80 177
state 1	1 278	15 622	777	141	645	1	18 464
state 2	291	608	6 765	800	855	0	9 319
state 3	1 338	58	517	34 449	1 475	1	37 838
state 4	1 009	616	775	1 361	13 534	355	17 650
state 5	1 815	0	0	1	240	12 700	14 756
Column Totals	80 732	17 937	9 321	37 841	17 654	14 734	178 204

The transition number matrices for 1991 and 1992 represent movement patterns before the fleet adjustment of 1993, while matrices for 1993 and 1994 are the post-adjustment matrices. The purpose of the adjustment through the restructuring of the composition of the fleet was to reduce effort. The absolute level of nominal effort in the post-adjustment period is certainly lower than that in the pre-adjustment period. Any differences between the relative deployment of effort between states are computed from transition probability matrices for the period 1991 through 1994. The pattern of deployment of nominal effort during the pre-adjustment period is not significantly different from that of the post-adjustment period, based on a chi-square goodness of fit test. Chi-square tests are, however, unlikely to reject an incorrect null hypothesis unless gross differences exist, thus making them weak tests of goodness of fit[9].

It is important to evaluate the significance of the differences in transition numbers observed in Tables 5.1 through 5.4. Although a goodness-of-fit test may be performed to provide an answer to this question, it is useful to consider that these matrices represent different season lengths, timing of closures and fleet composition. These factors must be 'controlled' before a more powerful goodness-of-fit test is possible.

It is in recognition of the different conditions under which the fleet movements reported in Tables 5.1 through 5.4 were produced that a transformation of these transition numbers to transition probabilities is considered. By considering the proportion of boats entering or leaving each of the six states we obtain a distribution of nominal effort that 'controls' for fleet size, season length and timing of closures. More important, the transformation is required for simulation and forecasts using the four-state fleet dynamics Markov model in Chapter 6. Tables 5.1 through 5.5 are, therefore, transformed to the transition probability matrices displayed in Tables 5.6 through 5.9. These matrices are then used for the test of goodness-of-fit. The results for the chi-square goodness of fit test using data from Tables 5.6 through 5.9 do not show any significant inter-annual differences in transition probabilities at the 5 percent level of significance.

[9] Other methods of testing goodness of fit can also be implemented here.

Table 5.6 suggests that about 17 percent (17.2%) of total nominal effort was allocated to fishing state 3 in the 1991 fishing period. About 10 percent (10.19%) of total nominal effort was allocated to state 1. The virtual transitions consistently comprise more than 70 percent of total nominal effort allocated to each destination state. Excluding state 0, we confirm that state 3 is clearly the most visited state and that state 2 is the least visited state in this period.

It is important to caution that the relative frequency cannot be interpreted as a direct measure of preferences for selected fishing grounds. This is because it may be the case that a certain level of aggregate nominal effort is optimal for a particular fishing ground, for a specified time period.

The interpretation given is, therefore, that the bio-economic conditions prevailing in the fishery in 1991, for example, created a scenario that attracted 10.19%, 6.38%, 17.2%, 6.8% and 8.74% of nominal effort for states 1 through 5, respectively. Similarly, fishing conditions in 1993 led to a deployment of 8.53%, 4.85%, 24.97%, 10.68% and 9.44% of nominal effort to states 1 through 5, respectively.

Table 5.6 Real and Virtual Annual Transition Probabilities for 1991

	TO					
FROM	**state 0**	**state 1**	**state 2**	**state 3**	**state 4**	**state 5**
state 0	0.9366	0.0148	0.007	0.013	0.009	0.0194
state 1	0.0886	0.8363	0.0489	0.008	0.0185	0
state 2	0.0338	0.0674	0.7387	0.0787	0.0814	0
state 3	0.047	0.003	0.0179	0.8984	0.0341	0
state 4	0.0664	0.0283	0.0707	0.0755	0.7268	0.0323
state 5	0.1256	0	0	0	0.012	0.8624
Destination Probabilities	0.507	0.1019	0.0638	0.172	0.068	0.0874

Table 5.7 Real and Virtual Annual Transition Probabilities for 1992

	TO					
FROM	state 0	state 1	state 2	state 3	state 4	state 5
state 0	0.9402	0.012	0.005	0.0135	0.011	0.0184
state 1	0.0674	0.8289	0.0465	0.007	0.05	0
state 2	0.0304	0.079	0.7036	0.0912	0.096	0
state 3	0.0392	0	0.0127	0.9048	0.042	0
state 4	0.0549	0.044	0.0327	0.0737	0.7757	0.0186
state 5	0.1264	0	0	0	0.021	0.8526
Destination Probabilities	0.476	0.096	0.044	0.2008	0.109	0.0739

Table 5.8 Real and Virtual Annual Transition Probabilities for 1993

	TO					
FROM	state 0	state 1	state 2	state 3	state 4	state 5
state 0	0.928	0.0126	0.007	0.0137	0.0138	0.0254
state 1	0.0688	0.8348	0.0512	0.0122	0.033	0
state 2	0.033	0.0568	0.684	0.132	0.0942	0
state 3	0.0326	0.002	0.0155	0.9121	0.0379	0
state 4	0.053	0.0284	0.0402	0.0821	0.7753	0.021
state 5	0.1212	0	0	0	0.0142	0.8646
Destination Probabilities	0.4152	0.0853	0.0487	0.2497	0.1068	0.0944

Table 5.9 Real and Virtual Annual Transition Probabilities for 1994

	TO					
FROM	state 0	state 1	state 2	state 3	state 4	state 5
state 0	0.9336	0.0113	0.005	0.0145	0.0127	0.0227
state 1	0.0492	0.8839	0.0229	0.0051	0.0387	0
state 2	0.0261	0.0542	0.7697	0.0481	0.1018	0
state 3	0.0229	0	0.009	0.9264	0.0415	0
state 4	0.0566	0.0342	0.0403	0.078	0.779	0.0118
state 5	0.1167	0	0	0	0.0196	0.8636
Destination Probabilities	0.387	0.1202	0.0515	0.2449	0.1201	0.0762

The mean and standard deviations for the real and virtual transition probabilities for the fishing period 1991 through 1994 are presented in Table 5.10. All the observed yearly transition probabilities are within ±2 standard deviations of their mean. For example, the average transition probability for transitions from state 3 to state 3, over the period 1991-94, is 0.9104 with a standard deviation of 0.0120. The smallest virtual transition probability for state 3, from the set of state 3 virtual transition probabilities for 1991 through 1994 is 0.8984, and is reported for the 1991 fishing season. This value is about one standard deviation of the mean probability of 0.9104[10]. The largest probability of 0.9264 for 1994 state 3 virtual transitions is less than two standard deviations from the mean[11].

Table 5.10 Mean and Standard Deviations of Real and Virtual Transition Probabilities (1991-1994)

		TO					
FROM		**state 0**	**state 1**	**state 2**	**state 3**	**state 4**	**state 5**
state 0	**Mean**	0.9346	0.0127	0.006	0.0137	0.0117	0.0215
	std dev	0.0052	0.0015	0.0011	0	0.0021	0.0032
state 1	**mean**	0.0685	0.846	0.0424	0.008	0.0351	0
	std dev	0.0161	0.0255	0.0131	0.003	0.0132	0
state 2	**mean**	0.0308	0.0643	0.724	0.0875	0.0934	0
	std dev	0.0035	0.0112	0.038	0.0348	0.0086	0
state 3	**mean**	0.0354	0.0016	0.0137	0.9104	0.0389	0
	std dev	0.0102	0.001	0.0039	0.012	0.0036	0
state 4	**mean**	0.0577	0.0338	0.046	0.0773	0.7642	0.0209
	std dev	0.0059	0.0076	0.0168	0.004	0.025	0.0085
state 5	**mean**	0.1225	0	0	0	0.0166	0.8608
	std dev	0.0045	0	0	0	0.0042	0.0055

[10] The calculation is: 0.9104-(1)(0.0120)=0.8984.
[11] The calculation is: 0.9264 < 0.9104+(2)(0.0120).

Table 5.11 shows the transition probabilities over the period 1991-1994 derived from the transition numbers in Table 6.5. As can be seen from observing Tables 5.10 and 5.11, the mean value of annual transition probabilities for the period 1991 through 1994 are not significantly different from the transition probabilities computed by adding all transitions for all states, for the period 1991-1994. This is confirmed at the 5 percent level of significance, in a chi-squared test of goodness of fit.

Table 5.11 Real and Virtual Annual Transition Probabilities for 1991-1994

	TO					
FROM	**state 0**	**state 1**	**state 2**	**state 3**	**state 4**	**state 5**
state 0	0.9354	0.0129	0.006	0.0135	0.0112	0.0209
state 1	0.0692	0.8461	0.0421	0.0076	0.0349	0
state 2	0.0312	0.0652	0.7259	0.0858	0.0917	0
state 3	0.0354	0.002	0.0137	0.9104	0.039	0
state 4	0.0572	0.0349	0.0439	0.0771	0.7668	0.0201
state 5	0.123	0	0	0	0.0163	0.8607

5.3 Characteristics of Transition Matrices

The simple goodness-of-fit test reported above is one way of establishing the similarity of stochastic matrices. An alternative method for indicating similarity involves comparing the special characteristics of the matrices. It is important to note that the simple goodness of fit test is the standard way of evaluating similarity. However, the evaluation of similarity of transition matrices using a comparison of special characteristics in the context of Markov modelling is novel.

This section is focussed on describing selected characteristics (as detailed in Section 4.5.3) of transition probability matrices for the six-state model. Interest is in examining the special characteristics of transition matrices in order to establish whether the stochastic matrices presented in Tables 5.6 through Table 5.10 possess similar properties. If their characteristics are similar, then data from which they are constructed are more likely to come from the same distribution. Furthermore, if a

Markovian process can, through simulation (see Chapter 6), produce results that are statistically similar to those presented in Table 5.6 through Table 5.10, then it can be concluded that the Markovian process can be used as a reliable process for modelling fleet dynamics in the NPF, provided historical fishing patterns reflect the future fishing behaviour well.

The special characteristics of the transition probability matrices are given in Tables 5.12 through 5.18. These include eigenvalues (Table 5.12), tests of definiteness (Table 5.13), eigenvectors (Table 5.14), orthogonality tests, norm and determinants (Table 5.15), singular values, (Table 5.16), characteristic polynomials (Table 5.17) and minimum polynomials (Table 5.18)[12].

Table 5.12 Eigenvalues of Observed Annual Transition Probability Matrices 1991 to 1994

Fishing Period	λ_1	λ_2	λ_3	λ_4	λ_5	λ_1
1991	1	0.653	0.747	0.91	0.833	0.857
1992	1	0.961	0.665	0.832	0.858	0.734
1993	1	0.645	0.924	0.827	0.75	0.853
1994	1	0.707	0.931	0.835	0.894	0.789
1991-1994	1	0.676	0.92	0.833	0.751	0.865

Table 5.13 Definiteness Tests of Observed Annual Transition Probability Matrices 1991 to 1994

	Fishing Period				
Characteristics	**1991**	**1992**	**1993**	**1994**	**91-94**
Negative definite	false	false	false	false	false
Negative semidefinite	false	false	false	false	false
Positive semidefinite	false	false	false	false	false
Positive definite	false	false	false	false	false

[12] It is noteworthy that these characteristics can be computed for any m-state Markov fleet dynamics model.

Table 5.14 Eigenvectors of Observed Annual Transition Probabilities 1991 to 1994

	Eigenvectors of Corresponding Distinct Eigenvalues λ_i					
Fishing Period	v_1	v_2	v_3	v_4	v_5	v_6
1991	0.857	0.833	1	0.747	0.653	0.91
1992	1	0.832	0.858	0.734	0.916	0.665
1993	0.645	0.924	0.853	0.827	0.75	1
1994	1	0.707	0.931	0.835	0.789	0.894
1991-1994	0.833	0.865	0.92	0.676	0.751	1

Table 5.15 Selected Characteristics of Observed Annual Transition Probability Matrices 1991 to 1994

	Fishing Period				
Characteristic	**1991**	**1992**	**1993**	**1994**	**91-94**
Rank	6	6	6	6	6
Trace	5	5.01	5	5.16	5.05
Condition Number	1.59	1.57	1.61	1.46	1.53
Determinant	0.317	0.32	0.315	0.388	0.337
Permanent	0.336	0.338	0.334	0.405	0.355
2-Norm	1.03	1.03	1.03	1.02	1.03
Orthogonality	false	false	false	false	false

Table 5.16 Singular Values of Observed Annual Transition Probability Matrices 1991 to 1994

	Elements of Diagonal Matrix					
Fishing Period	w_1	w_2	w_3	w_4	w_5	w_6
1991	0.819	0.701	0.789	0.893	0.94	1.02
1992	0.808	0.849	0.747	1.03	0.939	0.637
1993	1.03	0.658	0.734	0.811	0.927	0.854
1994	0.809	0.741	0.917	1.03	0.652	0.855
1991-1994	0.748	0.813	0.672	0.93	1.03	0.862

Table 5.17 Characteristic Polynomials of Observed Annual Transition Probability Matrices 1991 to 1994

	Coefficients of the Characteristic Polynomial						
Fishing Period	α_6	α_5	α_4	α_3	α_2	α_1	α_0
1991	1	-5	10.4	-11.4	7.07	-2.32	0.317
1992	1	-5.01	10.4	-11.5	7.11	-2.34	0.32
1993	1	-5	10.4	-11.4	7.06	-2.32	0.315
1994	1	-5.16	11.1	-12.6	8.06	-2.74	0.388
1991-1994	1	-5.05	10.6	-11.8	7.36	-2.44	0.337

Table 5.18 Minimum Polynomials of Observed Annual Transition Probability Matrices 1991 to 1994

	Coefficients of the Minimum Polynomial						
Fishing Period	α_0	α_1	α_2	α_3	α_4	α_5	α_6
1991	0.317	-2.32	7.08	-11.4	10.4	-5	1
1992	0.32	-2.34	7.12	-11.5	10.4	-5	1
1993	0.316	-2.32	7.07	-11.4	10.4	-5	1
1994	0.388	-2.75	8.07	-12.6	11.1	-5.16	1
1991-1994	0.334	-2.43	7.32	-11.7	10.5	-5.04	1

The results reported in Tables 5.12 through 5.18 suggest that the transition probability matrices, shown in Tables 5.6 through 5.9,

- all fail the tests of definiteness and orthogonality,
- have traces, determinants, condition numbers, and norms that differ by very small magnitudes;
- have singular values and characteristic polynomials that differ by very small magnitudes; and,
- have roots of the characteristic and minimal polynomials that are 'signed' in an identical manner.

Based upon these observations, it can be argued that the annual transition probability matrices and the mean of these annual transition probability matrices are similar and, therefore, that a similar process governs fleet movement in the NPF in each period. These results confirm the findings from the test of goodness of fit reported in Section 5.2. However, the additional importance of this second set of tests is that it also provides a list of properties that are necessary for numerical solutions that use stochastic matrices. For example, if the stochastic matrices are used for the purpose of forecasting or as part of an expression whose solution is desired, they must be nonsingular and have positive eigenvalues (Caswell 1989; Kreyszig 1993). In addition, these special characteristics are important for establishing the stability of the matrices (Kreyszig 1993). It is clear from Table 5.12 and Table 5.14 that these transition probability matrices have positive eigenvalues and are nonsingular. The results are consistent with those found for the four-state model. The transition matrices obtained using the four-state model can be used, therefore, for forecasting and simulation purposes in Chapter 6.

5.4 Testing Goodness of Fit using Daily Destination Vectors

The aim of this section is to establish whether the daily transitions arise from the same Markovian process. If the transitions indeed arise from a Markovian process, then destinations of vessels will be projected using a simulated Markov transition probability matrix and known starting vectors. Recall that the similarity of annual transition probability matrices was demonstrated using both goodness of fit tests, (see Section 5.2), and by examining special characteristics of stochastic matrices, (see Section 5.3). In this section, in order to show that the transitions are from a Markovian process, a goodness of fit test is applied to destination vectors. The destination vector shows the proportion of vessels in the respective states, at the end of a fishing day. It represents the incidence of fishers' daily fishing effort and is conditional on the initial vector and the daily transition probability matrix.

Table 5.19 reports the results of chi-square tests of the similarity of daily destination vectors for the banana prawn season for the years 1991 through 1994. The destination vector on a selected day, say day i=1, in 1994 is compared with the destination vector on the same day (day i=1) in 1991, 1992 and 1993.

Column 1 of Table 5.19 shows the fishing day and column 2 shows the chi-square value obtained by testing the goodness of fit of 1994 destination vectors on 1993 destination vectors. In other words, the null hypothesis is that the destination vector on day 1 in 1994 will be similar to the destination vector on day 1 of 1993. Similarly, the hypothesis is maintained that there will be no significant difference between the day 1 destination vector of 1994 and other previous year (1991,1992) day 1 destination vectors. The results show chi-square values less than 2, for the 1-by-6 destination vector for day 1 through day 68[13]. Significant differences in destination vectors are observed for the period day 69 to day 87. These differences correspond to the time period during which banana prawns are the targeted species.

Table 5.19 Chi-square Values: Banana Prawn Season 1991 through 1994

Day	94on93	94on92	94on91	93on92	93on91	92on91
1	0.08	0.09	0.16	0.12	0.04	0.11
2	0.07	0.01	0.01	0.06	0.06	0.01
3	0.19	0.06	0.07	0.13	0.09	0.02
4	0.09	0 04	0.09	0.13	0.13	0.02
5	0.11	0.04	0.11	0.07	0.11	0.28
6	0.21	0.11	0.2	0.13	0.22	0.58
7	0.59	0.19	0.61	0.12	0.07	0.66
8	0.43	0.28	1.02	0.19	0.29	1.11
9	0.6	0.29	0.85	0.74	3.37	1.07
10	1.02	0.3	0.49	0.76	4.04	0.87
68	1.23	5.74	0.9	0.66	1.05	0.21
69	1.51	25.85	25.65	11.88	11.75	0.02
70	0.08	27.86	26.75	21.46	20.07	0.01
71	0.15	38	30.8	26.45	20.18	0.01
72	0.19	36.89	33.29	28.14	23.96	0
80	1.16	35.72	35.21	25.14	24.73	0
81	2.99	33.51	33.51	21.22	21.22	0
82	10.95	26.81	26.81	0.08	0.08	0
83	21.32	27.59	27.99	0.01	0	0
84	18.58	24.29	24.29	0.01	0.01	0
85	19.61	25.67	25.43	0.01	0.02	0
86	12.03	16.56	15.71	0	0.02	0.02
87	0.08	0.14	0.02	0	0.02	0.02

[13] The chi-squared values for day 1 through 10 are shown above. The results for day 11 through 67 are also below 2. Only results for selected intervals are shown for ease of exposition. The plot for the chi-squared values for day 1 through 67 are shown graphically in Figure 5.4.

The results for the tiger prawn fishery, shown in Table 5.20, suggest no significant difference in destination vectors for the period dating from day 142 to day 243. The values of the goodness of fit tests, for this period are less than 2.0, and therefore confirm similarity of destination vectors of the early parts of the tiger prawn season. The chi-squared values for day 128 through 163 are statistically insignificant and have not been reported in Table 5.20. The chi-squared values for the interval day 120 through 244 are, however, shown graphically in Figure 5.5.

Table 5.20 Chi-squared Values: Tiger Prawn Season 1991 through 1994

	Fishing Periods Compared					
Fishing Day	**94on93**	**94on92**	**94on91**	**93on92**	**93on91**	**92on91**
122	0	0	0	0	0	0
123	30.67	6.74	5.81	0.34	0.27	0.23
124	24.32	9.04	7.12	0.28	0.51	0.43
125	14.8	11.21	10.39	0.17	0.84	0.58
126	8.69	9.67	10.39	0.03	0.76	0.61
127	11.62	9.67	10.39	0.03	0.37	0.29
164	0.4	0.13	1.31	0.26	0.36	0.47
165	0.43	0.12	1.09	0.36	0.66	0.46
166	0.43	0.23	0.26	0.29	0.59	0.12
167	0.27	0.2	2.14	0.22	1.11	0.65
168	0.36	0.21	1.02	0.18	0.16	0.39
169	3.04	0.32	2.01	0.24	0.21	0.62
170	1.94	0.22	0.98	0.11	0.12	0.43
171	1.53	0.18	0.64	0.11	0.1	0.09
172	1.63	0.38	1	0.07	0.17	0.22
173	1.43	0.19	0.93	0.14	0.3	0.22
174	1.21	0.14	0.68	0.16	0.28	0.16
175	0.92	0.11	0.42	0.07	0.14	0.11
176	0.82	0.11	0.33	0.19	0.28	0.1
177	1.19	0.22	0.79	0.14	0.34	0.15
237	0.28	0.5	2.77	0.1	0.83	0.58
238	0.25	0.51	1.14	0.09	0.32	0.17
239	0.17	0.47	0.87	0.12	0.28	0.14
240	0.35	0.62	0.94	0.07	0.18	0.11
241	0.47	0.78	0.94	0.07	0.2	0.15
242	0.66	0.89	1.08	0.09	0.14	0.12
243	1.08	1.43	1.26	0.03	0.09	0.17
244	3.48	4.28	2.64	0.03	0.26	0.14

The results displayed in Table 5.20 suggest that: low chi squared values for 92on91 indicate similarity of 1991 and 1992 destination vectors. Chi-squared values for 93on91 are generally higher than those for 93on92 indicating probable similarity of 1992 and 1993 transitions. Chi-squared values for 94on93 and 94on91 are generally higher than those for 94on92, indicating a stronger similarity of 1992 and 1994 destination vectors. The results presented in Table 5.19 and Table 5.20 are a subset of the results portrayed graphically in Figure 5.4 and Figure 5.5.

Figure 5.4 Chi-squared Values – Banana Prawn Season 1991 through 1994

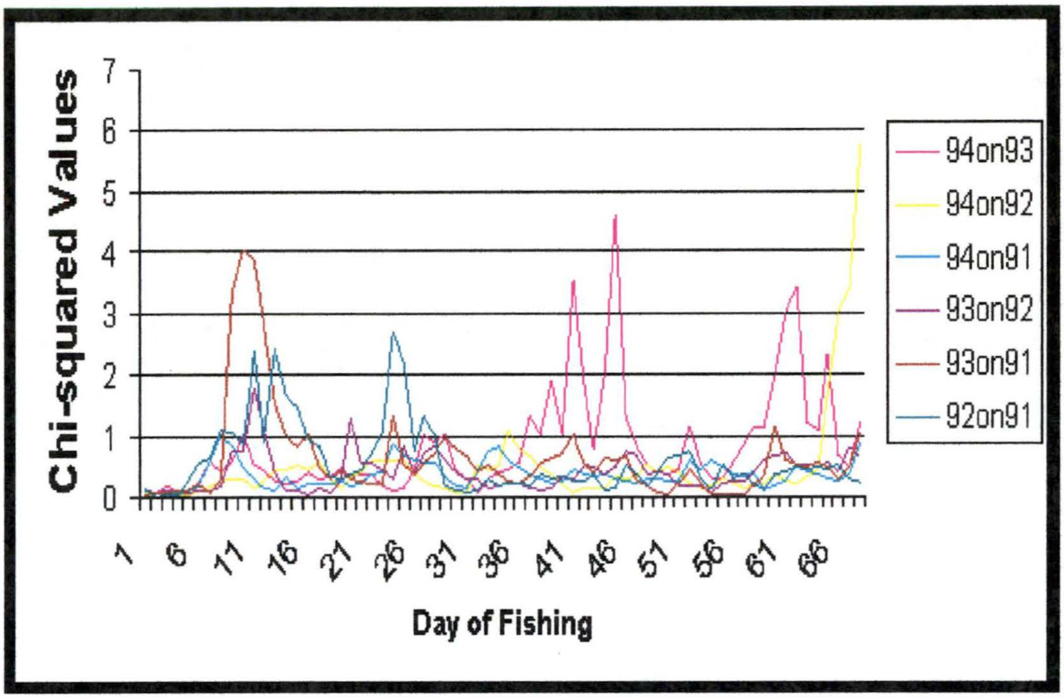
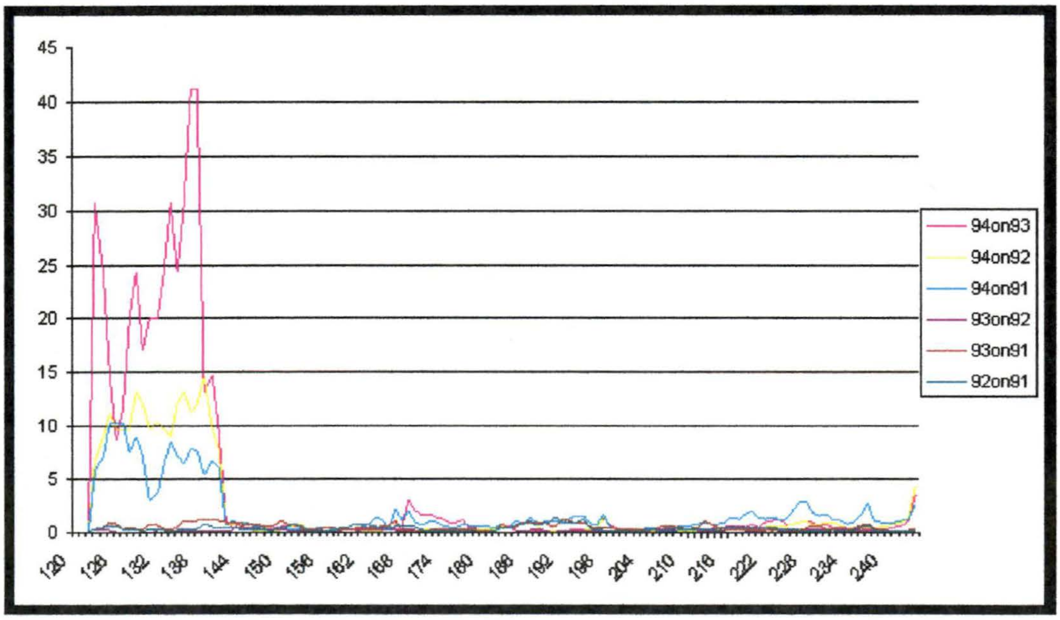


Figure 5.5 Chi-squared Values – Tiger Prawn Season 1991 through 1994



In order to project next day destinations, collective movements from one state to another over two fishing days are used to develop a fleet flow matrix. This flow matrix is then converted into proportions to create a transition matrix. To obtain the input vector, the number of vessels in different states is determined and the elements of the vector are then converted to a percentage. By adjusting the input vector or the proportion of vessels moving from different states into a selected fishing state, one can simulate the effect of policy decisions and determine their likely impact on future fishing patterns. The procedure is a very useful policy analysis tool. Although it is not a perfect predictive tool it allows quick assessment of the impact of a variety of management policies which may be modelled quite easily by manipulating the proportions in the Markov fleet dynamics model.

In the model presented in the thesis the states are defined in a way that is both useful for analysis of changes in policy and meaningful as a description of individual and aggregate behaviour. Short-run computations begin with a specified initial distribution and proceed iteratively. The Markov model projects past fleet movements into the future, assuming that the pattern of these movements extends into the future.

The resulting projections were then compared using a chi-square goodness of fit test at the 0.05 level of significance. Because the expected frequency in each class interval must be at least five for the application of the chi-square distribution, each state with a projected value of less than five was combined with the most logical neighbouring state to meet this requirement. The resulting combined states and computed chi-square values suggest no difference was found between the projected distribution of fleet by state and the actual distribution for the period 1991 through 1994. The probabilities indicate that most of the vessels are staying in the same fishing grounds, and that some vessels are advancing from one ground to another.

5.5 Estimates from the MNL Model

So far, this chapter has focused on transition probabilities based on historical fleet movements. From a modelling perspective, the transition probabilities are exogenous. In Section 4.6 the MNL model was presented as a means of explaining the evolution of transition probabilities. This model enables one to forecast changes in transition probabilities that arise from management policy and other changes. Although the usefulness of such an application for management purposes is dependent on the extent and quality of data available, an illustration of the principles of such an application is worthwhile for highlighting the economic decisions that underpin the Markov model used in this thesis.

Data on spatial and temporal variables, in particular, vessel-specific, skipper-specific and catch and effort variables (see Table 2.1 in Chapter 2) were used in estimating the parameters of the MNL model. The results of the MNL model of discrete choice in commercial fishing behaviour presented in Chapter 4 are presented in this section. These results are based on a three-state Markov model[14]. The parameters of the MNL model capture the effects of spatial and temporal variables on the fishers' choice of fishing ground. Most of the variables in the MNL model estimation for 1991 through 1994 fishing periods, yielded insignificant coefficients[15]. The model reported in this section includes only the calendar day of the month (DAYS) and the average daily catch of tiger (MTIGER) prawns in the selected fishing ground[16]. The calendar day is used as a simple way of introducing lunar periodicity in the ground choice probability model. Observations made by the researcher during a field trip in Australia's NPF, suggest that fishers make significant use of data on lunar periodicity in their decision making. It is their belief that different fishing grounds "fire-up" prior, during or following certain moon-phases. The estimated coefficients and the measures of fit are reported in Tables 5.21 through 5.25.

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[14] The four- and six-state models were also estimated. The results were similar to the results of the three-state Markov model. Only the results of the three-state Markov model are reported.

[15] Parameters of the MNL model were estimated using GAUSS (Aptech Systems 1992), and SHAZAM (SHAZAM 1993, 1997).

[16] Note that the variables DAYS and MTIGER produced statistically significant estimates.

Table 5.21 MNL Estimates of the Three State Ground Choice Model in 1991

Sample Size N=26728	Comparison	Logit Estimate	Standard Error	t-value	2-tailed Prob.	Exp
Constant	1/3	2.40538	0.7167	3.36	0.001	11.0826
	2/3	2.03976	0.7594	2.69	0.007	7.6888
DAYS	1/3	0.00611	0.0043	1.41	0.159	1.0061
	2/3	0.00604	0.0046	1.31	0.189	1.0061
MTIGER	1/3	-0.00185	0.0047	-0.39	0.695	0.9982
	2/3	-0.00494	0.0050	-0.99	0.323	0.9951

Table 5.22 MNL Estimates of the Three State Ground Choice Model in 1992

Sample Size N=22259	Comparison	Logit Estimate	Standard Error	t-value	2-tailed Prob.	Exp
Constant	1/3	5.26333	0.9521	5.53	0.000	193.1236
	2/3	5.30809	0.9947	5.34	0.000	201.9636
DAYS	1/3	-0.02127	0.0036	-5.99	0.000	0.9790
	2/3	-0.02323	0.0037	-6.23	0.000	0.9770
MTIGER	1/3	-0.02042	0.0082	-2.50	0.012	0.9798
	2/3	-0.02833	0.0085	-3.32	0.001	0.9721

Table 5.23 MNL Estimates of the Three State Ground Choice Model in 1993

Sample Size N=23320	Comparison	Logit Estimate	Standard Error	t-value	2-tailed Prob.	Exp
Constant	1/3	4.13358	0.5836	7.08	0.000	62.4012
	2/3	3.30237	0.5964	5.54	0.000	27.1771
DAYS	1/3	0.01342	0.0060	2.24	0.025	1.0135
	2/3	0.01489	0.0061	2.43	0.015	1.0150
MTIGER	1/3	-0.01051	0.0055	-1.90	0.058	0.9895
	2/3	-0.00971	0.0057	-1.72	0.086	0.9903

Table 5.24 MNL Estimates of the Three State Ground Choice Model in 1994

Sample Size N=26728	Comparison	Logit Estimate	Standard Error	t-value	2-tailed Prob.	Exp
Constant	1/3	6.19681	0.9146	6.78	0.001	491.1782
	2/3	5.68504	0.9352	6.08	0.001	294.4293
DAYS	1/3	-0.02718	0.0095	-2.85	0.004	0.9732
	2/3	-0.06674	0.0098	-3.46	0.001	0.9668
MTIGER	1/3	-0.01792	0.0057	-3.13	0.002	0.9822
	2/3	-0.01981	0.0059	-3.38	0.001	0.9804

The estimated parameters include the constant and they represent the effects of the day of fishing and the average catch of tiger prawns in the respective fishing ground on the choice of fishing ground[17]. It is noteworthy that the MNL model is identified by normalising the multinomial coefficients of one of the coefficients (Hall, Cummins & Schnake 1992, p.85). The interpretation of the effects of selected explanatory variables requires holding other explanatory variables constant at their mean values. In addition to interpreting the direct effects of explanatory variables on predicted probabilities, one may consider estimating the marginal effects of the explanatory variables on the predicted probabilities (Cramer 1991, Greene 1993; SHAZAM 1993, 1997). These marginal effects show how the probabilities change due to an instantaneous change in explanatory variables.

The results from the estimation of the model suggest a highly significant constant[18]. The extremely large t-ratio for the constant are as expected given the limitation on availability of data on several variables that influence the rational choice of fishing ground. It is clear that the use of only two variables, DAYS and MTIGER, to capture intricate decision making in Australia's NPF is bound to yield results of limited application. However, the explanatory variable DAYS and MTIGER are significant for the fishing periods 1992 through 1994. The coefficients of MTIGER for the pair-wise comparisons of fishing ground 1 to fishing ground 2, and fishing ground 2 to fishing ground 3 are negative and statistically significant for the fishing periods 1991 through 1994. The coefficients of DAYS for the pair-wise comparisons of fishing ground 1 to fishing ground 2, and fishing ground 2 to fishing ground 3 are negative and statistically significant for the fishing periods 1992 and 1994. The coefficients of the variables DAYS for the fishing periods 1991 and 1993 are positive and statistically significant at the 5 percent level.

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[17] Results are reported only for those variables that yield significant coefficients at the 5 percent level of significance. Discussion of the results is focused, therefore, on these variables and their relationship to the modelling framework.

[18] "The hypothesis that all the slope coefficients are zero is simple to test if the regression vector includes a constant term" Greene (1993, p.668).

The MNL model estimates obtained are reasonable probability estimates in spite of the dearth of spatial and temporal data used to estimate the coefficients[19]. The MNL model estimates predicted correctly between 64 and 69 percent of the ground choices in each of the fishing periods 1991 through 1994. In the case presented in Table 5.25 the data do not support the hypothesis that all the parameters in the model are zero. The predicted probabilities are also high and quite reasonable. At the 5 percent level of significance the test critical value is less than 6. Since in this case the likelihood ratio test statistics for the period 1991 to 1994 are greater than 6, the hypothesis that all the parameter values in the model are zero is rejected. The hypothesis that the average catch of tiger prawns (MTIGER) and the number of days before the end of the season (DAYS) have no effect on the probability of choosing a fishing ground is therefore rejected.

Other techniques such as simple Bayesian updating and even simple rules of thumb of vessel location may have produced such a high prediction rate. The difference, however, is that the MNL Markov allows other types of information, such as biological, economic and social data, to be incorporated.

The R-square values and related measures of goodness of fit are shown in Table 5.25[20]. Most practical applications involving discrete choice models the R^2 "range between 0.2 and 0.6" (Gujarati 1995, p.546). Very low values of R^2 suggest a clustering of variables around lower values of the predicted dependent variable (Cragg & Uhler 1970; Madalla 1993; Judge *et al.* 1985, 1988; Greene 1990, 1993; Griffiths, Hill & Judge 1993; Gujarati 1995; Shazam 1997). The R-square values are very weak in a majority of estimations, however. The R-square values shown in Table 5.25 would certainly improve if reliable data were collected on management, environmental and biological variables, data on characteristics of fishing grounds and fishing gear as well as data on fisher attributes and their response to management

[19] The measure of fit shown Table 5.25 is expressed in terms of the percentage of cases predicted correctly.
[20] Measures of goodness of fit in discrete choice models are computed using the likelihood ratio index (Cragg & Uhler 1970; Madalla 1993; Judge *et al.* 1985, 1988; Greene 1990, 1993; Griffiths, Hill & Judge 1993; Gujarati 1995; Shazam 1997).

strategies and actions. These results would certainly improve the value of the multinomial model of transition probabilities in describing and prediction fleet dynamics in Australia's NPF. For management strategy evaluation purposes it would be necessary to use catch in respective fishing grounds and temporal variables as key explanatory variables.

Table 5.25 Measures of Goodness of Fit (1991-1994)[21]

	Fishing Period			
Variable/Statistic	**1991**	**1992**	**1993**	**1994**
Test	**LRX²**	**LRX²**	**LRX²**	**LRX²**
Overall	12.5088	42.5737	7.411	17.5907
Constant	11.3725	31.3354	60.1459	46.9198
DAYS	2.0272	39.8794	5.9381	13.5712
MTIGER	1.7157	12.1243	3.64	11.4592
Percent Predicted	64.2941	67.2441	65.277	68.705
Madalla R^2	0.0005	0.0016	0.0003	0.0008
McFadden R^2	0.0003	0.001	0.0002	0.0005
Craig & Uhler R^2	0.0001	0.0004	0.0001	0.0002

Key
LRX^2 – The likelihood ratio test (chi-squared distribution)
Madalla R^2 – Madalla R-square goodness of fit measure (Madalla 1983)
Cragg-Uhler R^2 – Cragg-Uhler R-square - goodness of fit measure (Cragg & Uhler 1970)

[21] All tests are significant at the 5 percent level.

5.6 Estimates from the SUR Model

In Section 4.6.3 the SUR model was presented as a means of explaining the temporal evolution of aggregate transitions to fishing grounds. This model enables one to forecast changes in destination probabilities that arise from fishery-specific changes such as changes in catch rates, and management policy.

An ideal data set for estimating parameters of the SUR model should include variables in Table 3.1 (see Chapter 3), policy variables, as well as shot-by-shot data. In estimating the parameters of the SUR several variables were tried. Only those variables that yielded significant coefficients were reported[22]. The parameters of the SUR are estimated for the fishing periods 1991 through 1994, for the four-state fleet dynamics model. The four-state Markov model represents fishing within the Gulf of Carpentaria, fishing elsewhere in the NPF, fishing outside the NPF, and not fishing at all. The dependent variable in the SUR model for the fleet dynamics model is the number of fishers who selected a particular fishing ground as a destination for the day of fishing[23]. The explanatory variables used include the day of fishing (DAY), the month of fishing (MONTH), effects cycles of days (CYCLEDAY), and catch rates of tiger prawns (MTIGER) in the respective fishing grounds[24]. The variable, DAY, presents the ordering of days from the first to the last day of the fishing season and is used to capture the changes in destination probabilities over time. This variable and its coefficient have implications for fishery management. For example, a fishery management policy that alters the length of the fishing season on the basis of similarity between the current season and past seasons may consider the effects of this policy on the destination probabilities. The alteration of the length of the season may also be conditional. The effect of adjusting the length of the season will also depend on the timing of altering the length of the season.

[22] Parameters of the SUR were estimated using GAUSS (Aptech Systems 1993).
[23] In estimating the parameters of the four-state Markov model using SUR equations, the non-fishing state is excluded. The number of vessels targeting the non-fishing state is thus treated as a residual.
[24] For the purpose of evaluating fishery management it would be necessary to include explanatory variables that offer a broader measurement of effort.

The CYCLEDAY variable captures the changes in fleet movement during a particular day of the week, and is used to establish whether there is any evidence of the preference for particular fishing grounds during particular days of the week. The argument may be that some of the fishing state or fishing ground may not be preferred during certain periods of the week, as well as during the certain months. For example, the deployment of vessels during certain days of the week may depend on factors such as refuelling, crew changes and/or vessel maintenance and the incidence of recreational and congestion externalities. CYCLEDAY is included, therefore, as a way of finding out whether fishers make consistent choices over days of the week.

Similarly, the MONTH variable is used to check for changes in ground preferences over monthly intervals. It is important to consider such a variable given that banana prawns are predominantly caught in the earlier months of the season, while tiger prawns are caught predominantly in the later months of the season. It is quite likely, therefore, that the MONTH variable may capture changes in the fishers' ground choices triggered by changes in catch rates and relative prices of the targeted species. The management options that may be assessed using this model are limited to those that affect the length of season. If data were available on shot duration, number of shots, size of shots and bycatch, then management strategies related to effort controls could also be evaluated.

The results of the SUR estimations reported below are based on simple ordinary least squares (OLS) regression[25], and two types of SUR models, namely; the linear SUR model, and the restricted linear SUR model[26]. These three model specifications use the same regressors and regressands.

[25] It is useful to estimate simple OLS because the OLS estimates do not require the assumption of contemporaneous correlation. For differences between OLS and SUR see Greene (1993, p.488).
[26] In the restricted linear SUR model it is assumed that all coefficients are identical (see Griffiths, Hill & Judge 1993, p.554 for the conjecture on coefficient restrictions).

The results for the OLS estimation are reported in Tables 5.26 through 5.28[27]. The results for the linear SUR and the restricted linear SUR are reported in Tables 5.29 through 5.31 and Tables 5.32 through 5.34, respectively. The variables CATCH1, CATCH2 and CATCH3 represent catch rates in state 1, state 2 and state 3, respectively. In addition, DAY represents day of fishing, MONTH represents month of fishing, and CYCLEDAY represents a counter for day cycle. The standard error of the estimate (SE) and the Durbin-Watson statistic (DW) are included.

The results reported in Table 5.26 suggest that increasing catch rates in state1 had significant positive effect on destination probabilities to state 1 during the 1991 through 1994 fishing periods. Catch rates in state 3 had a significant positive effect on destinations to state 1, during the fishing periods 1991, 1992 and 1994. A significant negative effect is recorded for the 1993 fishing period. In other words catch rates in ground 3 in 1993 encouraged fishers to exit ground 1. The relative return per unit of fishing effort in state 1, in 1993, may have been fairly marginal. The results also suggest that there was a tendency for fishers to exit state 1 towards the end of the 1992 fishing seasons. The effect was different for the 1991, 1993 and 1994 fishing periods. Fishers stayed longer in state1 during these fishing periods.

An increase in catch rates in state 3 does not seem to have encouraged fishers to enter ground 2. The coefficient of CATCH2 in the model predicting destinations to state 3 is negative and statistically significant, for the fishing periods 1991, 1993 and 1994. The MONTH effect prompted an exodus of vessels from ground 2 in fishing periods 1991 through 1993. Similar interpretations can be made from Tables 5.27 through 5.34[28].

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[27] These tables refer to a three-fishing state Markov model because the non-fishing state has been excluded as suggested earlier, in a footnote.

[28] Most estimates presented in Tables 5.26 through 5.34 are statistically significant at the 5 percent level.

TABLE 5.26 OLS Regression Estimates of State 1 Transitions 1991 – 94

	Fishing Period							
Period	1991		1992		1993		1994	
	estimate	t-value	estimate	t-value	estimate	t-value	estimate	t-value
Constant	-0.7765	-0.6815	34.6725	33.7394	34.5649	69.2067	35.4979	62.5011
CATCH1	0.0670	115.5275	0.1250	96.6140	0.0356	84.5271	0.1111	106.6869
CATCH3	0.0144	39.4857	0.0154	37.3029	-0.0145	-24.8532	0.0105	15.0565
DAY	0.3744	106.3689	0.3443	102.1181	0.0907	39.2250	0.1819	90.0143
MONTH	2.3340	23.1277	-1.2806	-12.9876	4.2013	66.4139	0.0050	0.3113
CYCLEDAY	0.1169	4.5234	0.4454	17.9288	0.2125	16.2736	1.1220	20.6451
Sample Size		25514		26728		22259		23320
R-squared		0.4280		0.3850		0.5150		0.4500
SE		34.8610		36.5070		16.5320		20.7260
DW		0.1790		0.3750		0.4160		0.1560

Note:
Catch variables which were not significant in the various regression models, were excluded from the several iterations of the models.

TABLE 5.27 OLS Regression Estimates of State 2 Transitions 1991 – 94

	Fishing Period							
	1991		1992		1993		1994	
	Estimate	t-value	estimate	t-value	estimate	t-value	estimate	t-value
Constant	37.1461	123.3497	34.4121	108.3178	31.1486	124.8747	26.9369	128.6915
CATCH3	0.0063	48.6330	-0.0001	-0.3794	0.0303	91.3576	0.0191	67.5276
MONTH	-2.7185	-78.6989	-2.2581	-59.3823	-2.2513	-79.4697	0.0296	4.2850
CYCLEDAY	-0.0643	-6.9347	0.0629	6.5320	0.1784	22.8238	-1.9672	-92.2607
Sample Size		25514		26728		22259		23320
R-squared		0.0580		0.1210		0.4990		0.4420
SE		4.2500		14.5280		10.0470		8.8750
DW		0.2400		0.0770		0.6660		0.3080

Note:
Catch variables which were not significant in the various regression models, were excluded from the several iterations of the models.

TABLE 5.28 OLS Regression Estimates of State 3 Transitions 1991 – 94

	Fishing Period							
	1991		1992		1993		1994	
	Estimate	t-value	estimate	t-value	estimate	t-value	estimate	t-value
Constant	4.0743	41.1735	3.8702	53.6913	1.2249	41.4825	1.1483	43.4283
CATCH3	0.0012	27.9696	0.0008	22.1500	0.0037	94.4041	0.0034	96.3245
MONTH	-0.2267	-19.9748	-0.3095	-35.8689	-0.1342	-40.0209	-0.0017	-1.9363
CYCLEDAY	0.0338	11.0982	0.0060	2.7564	0.0222	24.0123	-0.1067	-39.5959
Sample Size		25514		26728		22259		23320
R-squared		0.0580		0.0750		0.4040		0.3830
SE		4.2500		3.2960		1.1890		1.1210
DW		0.2400		0.2080		0.8980		0.6640

Note:
Catch variables which were not significant in the various regression models, were excluded from the several iterations of the models.

TABLE 5.29 Linear SUR Estimates of State 1 Transitions 1991 – 94

	Fishing Period							
	1991		1992		1993		1994	
	Estimate	t-value	Estimate	t-value	estimate	t-value	estimate	t-value
Constant	-6.3709	-5.6570	43.2475	44.0080	32.5834	71.8910	36.1031	70.5310
CATCH1	0.0802	141.8510	0.1336	106.9680	0.0328	82.9210	0.1225	123.9870
DAY	0.3734	107.1750	0.3129	95.1070	0.0986	44.4510	0.1775	92.3070
MONTH	2.8849	27.9750	-1.6656	-16.6830	4.3209	67.6790	-0.0381	-2.3660
CYCLEDAY	0.3161	11.9410	0.4418	17.4010	0.1859	14.0640	1.0202	18.8760
Sample Size		25514		26728		22259		23320
R-squared		0.3840		0.3520		0.4970		0.4410
SE		36.1670		37.4750		16.8361		20.8940
DW		0.1140		0.2910		0.3700		0.1480

Note:
Catch variables which were not significant in the various regression models, were excluded from the several iterations of the models.

TABLE 5.30 Linear SUR Estimates of State 2 Transitions 1991 – 94

	Fishing Period							
	1991		1992		1993		1994	
	Estimate	t-value	estimate	t-value	Estimate	t-value	estimate	t-value
Constant	51.0747	123.4230	44.0108	128.4810	44.9434	167.4940	35.5613	197.0230
CATCH2	-0.0060	-21.8610	-0.0048	-11.9360	-0.0077	-57.1190	-0.0014	-9.5240
DAY	-0.0607	-48.5740	-0.0869	-74.7740	-0.1056	-81.3440	-0.0824	-116.3360
MONTH	-3.0216	-81.8970	-1.8523	-52.9210	-1.4028	-37.7840	0.0238	3.9900
CYCLEDAY	-0.0789	-8.5860	0.0249	2.8290	0.1465	19.2190	-1.3132	-65.9120
Sample Size		25514		26728		22259		23320
R-squared		0.2900		0.2700		0.5180		0.2500
SE		12.8050		13.2460		7.6880		12.1840
DW		0.1110		0.1080		0.2330		0.7060

Note:
Catch variables which were not significant in the various regression models, were excluded from the several iterations of the models.

TABLE 5.31 Linear SUR Estimates of State 3 Transitions 1991 – 94

	Fishing Period							
	1991		1992		1993		1994	
	Estimate	t-value	estimate	t-value	Estimate	t-value	estimate	t-value
Constant	4.6163	43.1100	4.6546	59.9310	1.3769	47.8260	1.4364	54.2350
CATCH3	0.0005	11.9620	0.0007	20.1110	0.0025	67.9930	0.0029	79.1290
DAY	-0.0017	-4.5790	-0.0082	-28.3720	-0.0055	-36.7460	-0.0039	-37.4870
MONTH	-0.2430	-21.2730	-0.2668	-31.2170	-0.0485	-10.9170	-0.0010	-1.1340
CYCLEDAY	0.0362	11.9050	0.0029	1.3540	0.0223	24.6480	-0.0676	-23.6580
Sample Size		25514		26728		22259		23320
R-squared		0.0400		0.1050		0.4160		0.4150
SE		4.2711		3.2440		1.1780		1.0920
DW		0.2110		0.2130		0.6580		0.5920

Note:
Catch variables which were not significant in the various regression models, were excluded from the several iterations of the models.

TABLE 5.32 Restricted Linear SUR Estimates of State 1 Transitions 1991 – 94

	Fishing Period							
	1991		1992		1993		1994	
	Estimate	t-value	estimate	t-value	estimate	t-value	Estimate	t-value
Constant	92.7971	93.3230	97.5246	102.9600	50.3232	109.9040	63.9637	118.7480
CATCH1	0.0024	24.7350	0.0017	24.9030	0.0018	55.9710	0.0028	48.4290
DAY	0.1547	43.6360	0.2246	62.4430	0.0460	18.6590	0.1292	58.3150
MONTH	-2.2177	-20.1760	-3.7990	-34.3770	4.1731	56.1400	0.0691	3.6440
CYCLEDAY	-0.5592	-19.0710	-0.1169	-4.1640	0.0132	0.8680	0.8786	13.8080
Sample Size		25514		26728		22259		23320
R-squared		0.0960		0.1440		0.3200		0.1950
SE		43.8130		43.0700		19.5710		25.0860
DW		0.1310		0.1190		0.3680		0.1700

Note:
Catch variables which were not significant in the various regression models, were excluded from the several iterations of the models.

TABLE 5.33 Restricted Linear SUR Estimates of State 2 Transitions 1991 – 94

	Fishing Period							
	1991		1992		1993		1994	
	Estimate	t-value	estimate	t-value	estimate	t-value	estimate	t-value
Constant	42.4839	115.7330	41.2387	136.8780	35.0431	129.7690	33.7088	172.6500
CATCH2	0.0024	24.7350	0.0017	24.9030	0.0018	55.9710	0.0028	48.4290
DAY	-0.0423	-32.9360	-0.0822	-72.0560	-0.0764	-52.8420	-0.0783	-98.0260
MONTH	-2.5837	-65.2640	-1.7614	-50.3020	-1.3237	-30.4020	0.0077	1.1260
CYCLEDAY	-0.0381	-3.6350	0.0352	3.9630	0.2014	22.6440	-1.2981	-56.7510
Sample Size		25514		26728		22259		23320
R-squared		0.2430		0.2710		0.3600		0.5600
SE		13.2290		13.2390		11.3490		7.8810
DW		0.0960		0.0980		0.1300		0.2260

Note:
Catch variables which were not significant in the various regression models, were excluded from the several iterations of the models.

TABLE 5.34 Restricted Linear SUR Estimates of State 3 Transitions 1991 – 94

	Fishing Period							
	1991		1992		1993		1994	
	Estimate	t-value	estimate	t-value	estimate	t-value	estimate	t-value
Constant	3.0669	11.8280	3.9026	25.4890	1.5627	53.8480	1.4470	32.3520
CATCH3	0.0024	24.7350	0.0017	24.9030	0.0018	55.9710	0.0028	48.4290
DAY	0.0035	3.7800	-0.0059	-10.3130	-0.0062	-40.4510	-0.0039	-22.2570
MONTH	-0.1992	-7.2160	-0.2343	-13.8350	-0.0554	-12.1760	-0.0011	-0.7390
CYCLEDAY	0.0295	4.0060	0.0054	1.2650	0.0229	24.6600	-0.0680	-13.9680
Sample Size		25514		26728		22259		23320
R-squared		0.0280		0.0690		0.3840		0.4150
SE		4.3170		3.3080		1.2090		1.0920
DW		0.3360		0.2830		0.5230		0.5900

Note:
Catch variables which were not significant in the various regression models, were excluded from the several iterations of the models.

The use of the SUR in Markov modelling requires showing the link between catch and effort, spatial and temporal ground choices, and most important, the existence of contemporaneous correlation in ground choice. The following key findings can be drawn from the results of the SUR estimation. The MONTH effect is consistently significant for all states across all fishing grounds. Catch rates in state 2 have no prominent effect in determining destination probabilities in state 2. There is very little difference between the statistical significance of parameters estimated under simple OLS, linear SUR and restricted linear SUR. This suggests that the system can also be estimated directly using three-stage least squares. The results suggest that there is little empirical evidence to suggest a need to assume contemporaneous correlation.

5.7 Concluding Remarks

In general the results shown in Tables 5.1 through 5.11 show a concentration of relocations on virtual transitions. Where real transitions occur they are to a small number of fishing grounds in the neighbourhood of the current fishing ground. These results suggest that the current location choices of the fleet are related strongly to previous location of vessels and the accessibility and catch rates in the fishing grounds in the neighbourhood of the current fishing ground.

The pattern of deployment of nominal fishing effort is similar for the periods 1991 through 1994. The level of allocation of effort (that is, the actual number of vessels being deployed) is not significantly different between any of the sample periods. The results are consistent with the observed transitions having come from a Markov process. The most immediate transition probability matrix (for example, previous day transition probability or previous year annual transition probability) forecast future transition probability matrices consistently better than transition matrices from the remote past. The results in Tables 5.12 through 5.18 show a consistent pattern of the special characteristics of the transition matrices, suggesting that the observed fishing process may be reasonably stable. The testing of goodness of fit using destination vectors (Tables 5.19 through 5.20) and the projections thereof, are statistically significant, suggesting that the mechanism displayed can produce reliable estimates of likely vessel movements. Results reported in Tables 5.21 through 5.24 show significant effects of the day of fishing and the average catch of tiger prawns. It is on this basis that the researcher argues that fishing patterns in Australia's NPF are Markovian. It is important to note that the tests of similarity are used to compare forecasts derived from simulation experiments in Chapter 6.

Estimates of coefficients of both the MNL and SUR regressions explaining transition probabilities are also reported in this chapter. The purpose of estimating these regressions for the NPF was to provide the empirical basis upon which to update transition probabilities, in response to changes in policy variables, as part of an enhanced Markov simulation procedure. However, although the estimated results are useful, the included temporal variables cannot be used to simulate a change in fishery policy due to assumptions relating to fleet aggregation and homogeneity implied in the SUR model. Simulations presented in Chapter 6, therefore, are for an illustrative example in which a MNL model specification and coefficient estimates are postulated.

CHAPTER 6

SIMULATING FLEET DYNAMICS IN THE NPF

6.1 Introduction

In Chapter 5 the characteristics of the transition matrices for different fishing periods were presented and compared. The purpose of evaluating the characteristics of the matrices was to identify the degree of similarity in transitions between all available states and so ascertain the closeness of fleet fishing patterns in one fishing period to fishing patterns in another fishing period. If fishing patterns in any two or more fishing periods are similar it is argued that, by implication, reliable forecasts of fleet movements in the subsequent time periods could have been formed from past time periods. Such past time periods may exhibit similar features in terms of their meteorological, oceanographic, institutional or economic characteristics, among others. In addition to the presentation of transition matrices and their characteristics for an ordinary Markov model, the results of estimating a simple MNL model for the NPF were also presented. This followed the development in Chapter 4 of an enriched Markovian (MNL Markov) framework in which endogenous transition probabilities are updated based on estimates of the MNL model of ground choice[1].

In this chapter forecasts of likely vessel movements and simulations of fleet movement for various fishery management policy changes are presented and discussed. The simulations are based on the fishers' ground choices and the level of participation in the selected fishing ground, and results are reported for both the ordinary and the MNL Markov models. All forecasts and simulations are done within the context of a four-state fleet dynamics model representing the non-fishing state (state 0), fishing in the Gulf of Carpentaria (state 1), fishing elsewhere within the NPF (state 2), and fishing outside the NPF (state 3). The four states are chosen because they represent the main areas of fishing.

[1] The SUR results reported in Chapter 5 can also be used to enrich the Markov model as explained in Chapter 4. The MNL model is preferred to the SUR approach, and is used to enrich the Markov model in this thesis. This is because the MNL model uses individual level data and is not constrained by the assumption of homogeneous fishers.

Note, however, that when analysing fishery policy managers would probably require a higher-order state model and data of greater spatial and temporal resolution. The four states considered are defined for all fishing days of the fishing season.

Sixteen transitions are therefore possible, and include transitions (i) from state 0 to state 0 (a 0-0 transition), suggesting no fishing in two consecutive days; (ii) from state 0 to state 1 (a 0-1 transition), suggesting fishing in the Gulf of Carpentaria on the second day of the two consecutive days; (iii) from state1 to state1 (a 1-1 transition) suggesting continued fishing in the Gulf of Carpentaria over two consecutive days; and, (iv) from state 3 to state 3 (a 3-3 transition) suggesting continued fishing outside the NPF over two consecutive days. These transitions are denoted τ_{00}, $\tau_{01,}$ $\tau_{11,}$ and τ_{33}, respectively. It is noteworthy that since the non-fishing state is included the number of vessels in forecasts and simulations is constant for a particular fishing period.

The ordinary and MNL Markov models of fleet dynamics require (i) a daily starting vector, and (ii) a transition probability matrix. These two matrices are used to compute the daily destination vector. The elements of the starting vector and transition probability matrix in the MNL Markov depend, among other things, on a range of physical, biological, economic and management policy factors[2]. For example, the number of vessels operating in the fishery, the number of alternative high-yielding fishing grounds in the neighbourhood of the current fishing ground, management requirements[3], off-season activities of skippers, the pattern of ownership of vessels, the number of fishing grounds open, the number of days before the end of the fishing season, classes of vessels, routine maintenance work on vessels, and the traditional vantage starting positions (which are conditional on catch and weather conditions), all lead to considerable variation in the port choices of fishers and will be reflected in the probability of particular spatial and temporal movements.

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[2] Fishers may decide to relocate to an alternative ground on the basis of an expectation that CPUE per boat is likely to decline and that the net marginal benefit of fishing elsewhere is higher than that of staying in the current fishing ground.

[3] The closure of particular fishing grounds may induce fleet relocation.

It is important that fishery managers understand the way in which various policy measures will affect fleet movement. Updating transition probabilities in the Markov model, to reflect changes in the behaviour of vessels in response to changes in policy, is important in accurately predicting fleet dynamics. Updating Markov transition probabilities can be done using estimates from the MNL model in which appropriate policy variables are included. An MNL model and related parameter values are postulated and used to illustrate how MNL Markov simulations are conducted[4]. The results of these illustrative simulations are then compared with results from simulations based upon the ordinary Markov model in which transition probabilities are invariant to changes in fishery management policy.

The rest of Chapter 6 is organised as follows. Forecasts of fleet movements in any fishing season using data from past fishing seasons are presented in Section 6.2. A description of how the forecasts are made is presented in Section 6.2.1, and the results of the forecasts are reported in Section 6.2.2. Tests of reliability of these forecasts are reported and discussed in Section 6.2.3. These measures of reliability use standard error analyses. The analysis is extended further in Section 6.2.4, by introducing a lag structure into a model as an alternative to the ordinary Markov model. The purpose of the lag structure analysis is to evaluate the dominance of Markov forecasts.

Simulations of fleet movement in the NPF in response to fishery policy changes are presented in Section 6.3. The fishery management policies considered are (i) closing selected fishing grounds, and (ii) shortening the length of the fishing season. These policies are simulated using a general method described in Section 6.3.1. The estimating equations and the postulated MNL coefficients required are shown in Section 6.3.2.

[4] The inability to include a relevant policy variable in the estimation reported in Chapter 5, and the generally weak results of the estimation mean that actual MNL estimates are not used in the current simulations. This clearly restricts the extent to which policy recommendations can be drawn from the simulation results.

The illustrative results of simulating the effects of fishery management policies, under the assumption of MNL Markov and ordinary Markov transition probabilities, are presented in Sections 6.4. Results presented in Section 6.4.1 show the likely effects of closing selected fishing grounds. Results presented in Section 6.4.2 show the likely effects of shortening the length of the fishing season. Results of more complex composite policies are presented in Sections 6.4.3 and 6.4.4. Results from simulating ground closure using daily ordinary Markov transitions are reported in Section 6.5. Concluding remarks are drawn in Section 6.6.

6.2 Forecasting Fleet Movements in the NPF

In this section results of vessel and fleet level forecasts are reported. Recall that in forecasting fleet movement it is assumed that all transitions in one fishing period can be replicated using transition probabilities, if a starting vector is known. The intention is to predict likely future vessel movements using information on fleet dynamics from past fishing periods.

6.2.1 Description of Method of Forecasting Fleet Movement

In this section, daily transition probability matrices in previous periods are used to forecast future vessel destinations, using a random number generator[5] and known current period starting vectors. For example, in Figure 6.1 the proportion of vessels targeting state 1 or state 2 in 1992 is calculated using known starting positions in 1992 and historical transition probabilities observed in 1991. In this case, since information on 1991 movements is available, the problem of forecasting 1992 movements is reduced to establishing the proportion of vessels targeting each state conditional on past transitions and current starting positions. It is noteworthy that different series of historical probability matrix will yield different forecast destinations.

[5] Two random numbers between 0 and 1are selected. The first number is used to identify the starting position of a vessel. The second random number is used to identify the transition the vessel is likely to make, conditional of the vessel's starting position.

In this exercise, the transition probability matrices for 1991 is used to forecast movements in 1992. Transition probability matrices for 1991 and 1992 are used to forecast 1993 vessel movements. Similarly, transition probability matrices for 1991, 1992 and 1993 fishing periods are used to forecast the number of vessels likely to target particular states in 1994.

6.2.2 Results of Forecasting Fleet Movement

Figures 6.1 through 6.6 show the daily forecasts of fleet movement for 1991 through 1994. Note that forecasts for only two states, namely state 1 (fishing in the Gulf of Carpentaria) and state 2 (fishing elsewhere in the NPF), are reported. These two states have been chosen because they tend to have higher participation levels than states 0 or 3. In addition, the general conclusions that emerge from state 1 and state 2 forecasts are similar to those that arise from observing forecasts for state 0 and state 3.

Figures 6.1 through 6.6 show the series hstate1, hstate2, sstate1, and sstate2. The series hstate1 and hstate2 represent the observed historical movements to state1 and state2, respectively. The series sstate1 and sstate2 represent the simulated movements to state1 and state 2, respectively. The results show only the forecasts for days during which the fishery was open in both seasons (see Table 3.3 in Chapter 3). Figure 6.1 shows forecasts of 1992 fleet movements based on 1991 movements. Figures 6.2 and 6.3 show 1993 forecasts using 1991 and 1992 data, respectively. The results displayed in Figures 6.4 through 6.6 show forecasts for 1994 destinations that are based on 1991, 1992 and 1993 probability matrices, respectively.

Results displayed in Figure 6.1 suggest that the elements of the series of forecast movements to state 1 (sstate 1) are close to the elements of the series of historical transitions to state 1 (hstate 1). The series of forecast transitions to state 2 (sstate 2) are also close to the series of observed (historical) transitions to state 2 (hstate 2). This suggests, that 1992 fleet movements, in a four state Markov model, can be evaluated reliably using 1991 transition data. The results displayed in Figure 6.2 show quite marked differences between the time paths of the historical and simulated series. The differences between the hstate 1 and sstate1 or between hstate 2 and sstate 2 series in forecasts of 1993 fleet movements using 1992 transitions displayed in Figure 6.3 are smaller than those shown in Figure 6.2. This would seem to suggest that forecasts of transitions from the most recent fishing period tend to be better than those based on transitions in more remote fishing periods.

Figure 6.1 Forecasting Fleet Movement in 1992 using 1991 Transitions

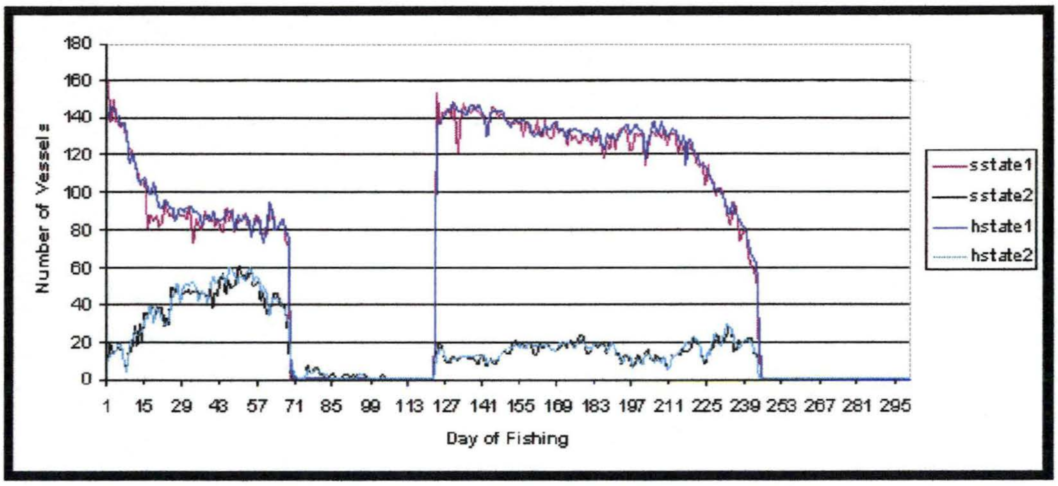


Figure 6.2 Forecasting Fleet Movement in 1993 using 1991 Transitions

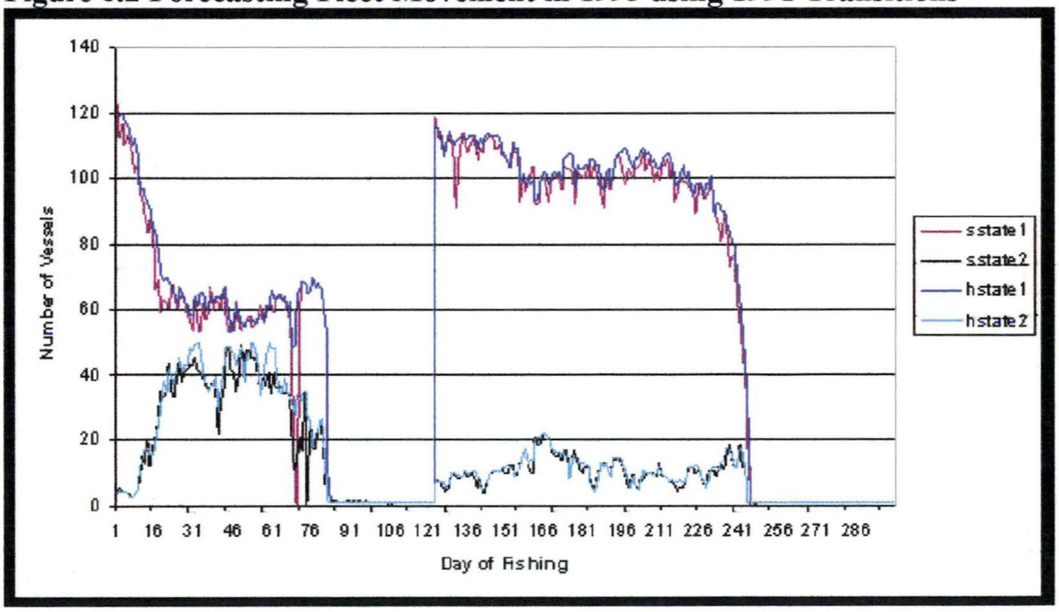


Figure 6.3 Forecasting Fleet Movement in 1993 using 1992 Transitions

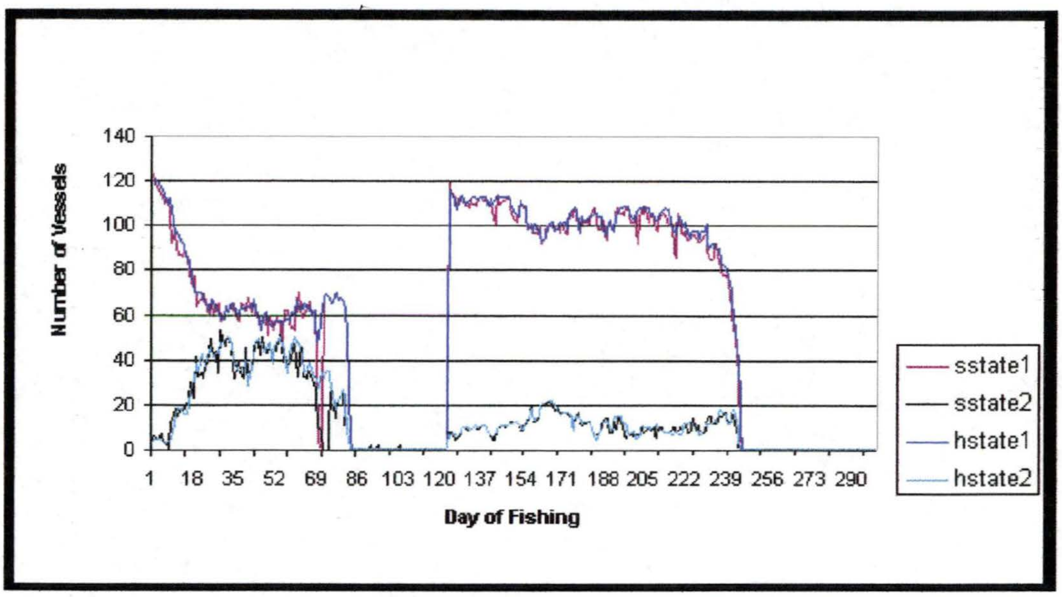


Figure 6.4 Forecasting Fleet Movement in 1994 using 1991 Transitions

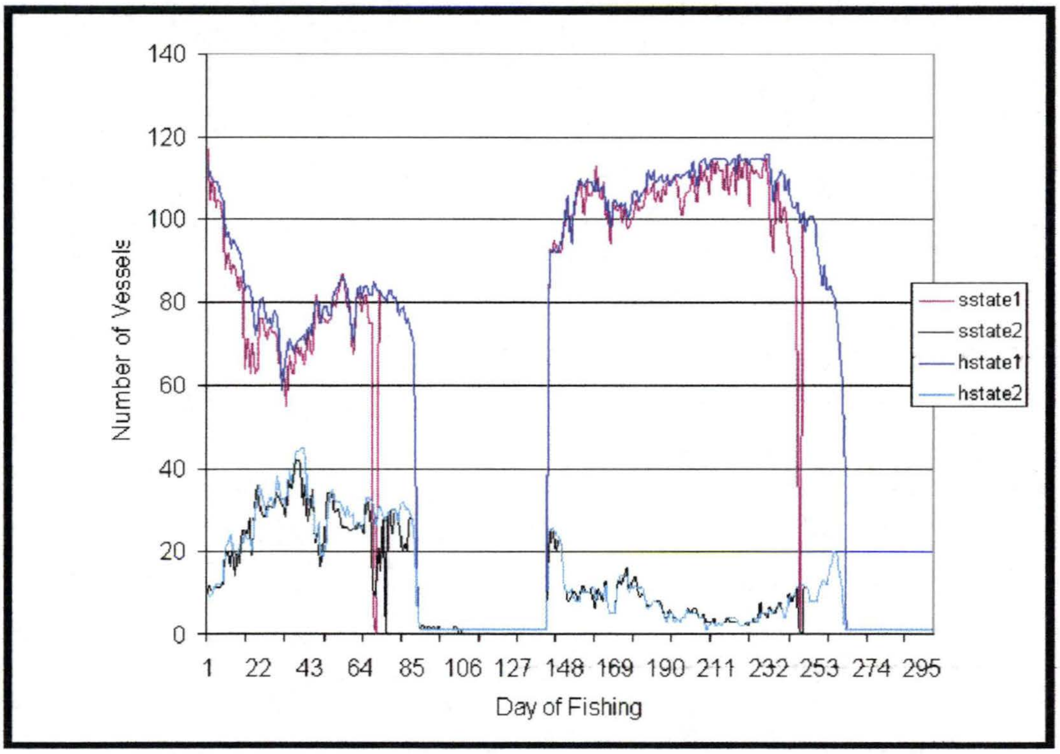


Figure 6.5 Forecasting Fleet Movement in 1994 using 1992 Transitions

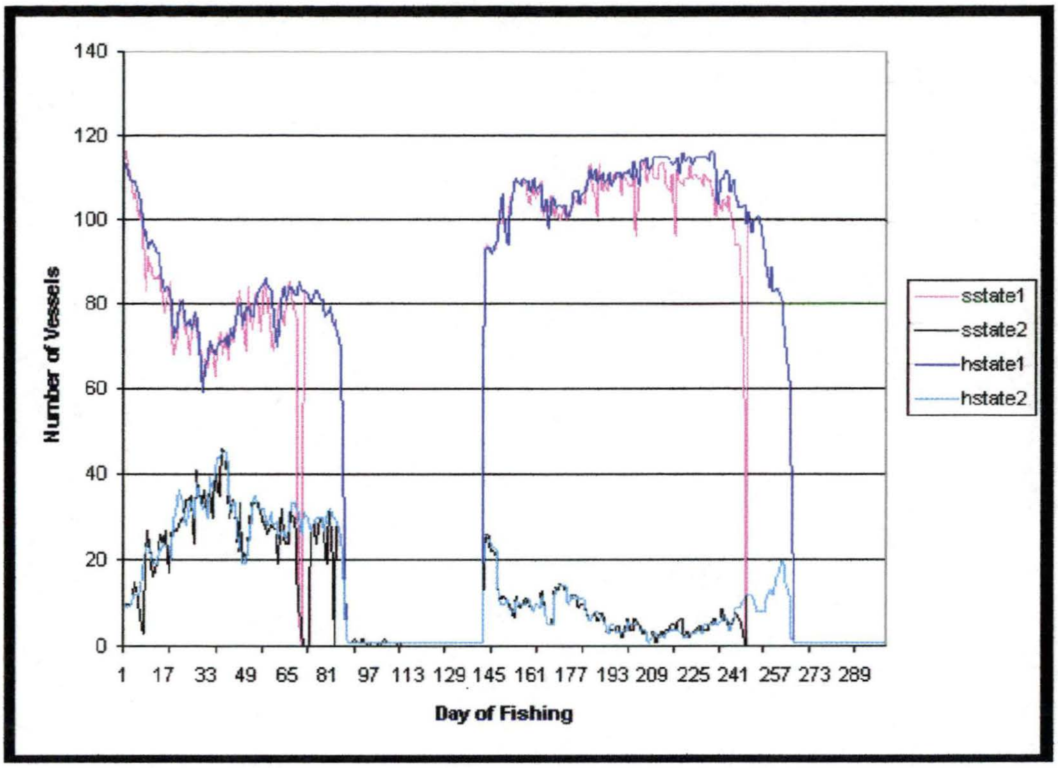
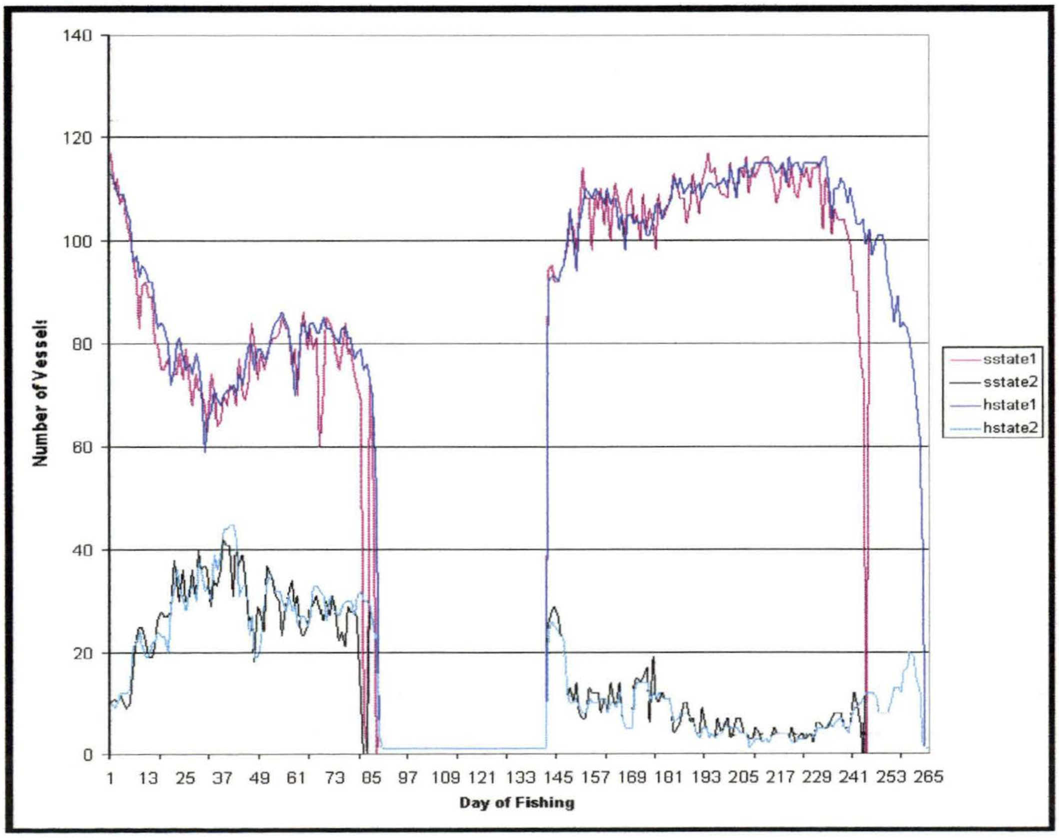


Figure 6.6 Forecasting Fleet Movement in 1994 using 1993 Transitions



The differences between the simulated and historical series are more pronounced in Figures 6.4 through 6.6, which show forecasts of 1994 based on 1991, 1992 and 1993 data. However, forecasts of 1994 transitions based on 1993 data (see Figure 6.6) are closer to their historical counterparts than are forecasts based on 1992 transitions (see Figure 6.5), or forecasts based on 1991 data (see Figure 6.4).

The results most likely reflect the similarity of conditions such as prawn recruitment and catch rates, weather conditions, oceanographic phenomena or management changes that account for differences in fleet dynamics across fishing periods. The graphs indicate that forecasts based on the most recent fishing period tend to give more reliable estimates than forecasts based on more remote fishing periods. For fishery managers the choice of similar fishing periods is important since forecasts of future vessel movements can be derived reliably using movements from similar fishing periods. For example, suppose the position of vessels on day i of the 1992 fishing period is known. Suppose the vessel movements or transition probabilities in 1991 are considered a good proxy for likely transitions in 1992, based on meteorological, oceanographic as well as catch history data. Then, the destination vector of day i+1 of the current year can be computed by finding the product of the transition probabilities reflected in the proxy year by the starting vector observed in the current fishing period.

6.2.3 Testing the Reliability of Forecasts

The graphs presented in Figure 6.1 through 6.6 give a visual impression of the closeness of fit of the forecasts generated. It is useful, however, to consider quantitative measures of evaluating forecasts. The quantitative measures used in evaluating forecasts are (i) mean error (ME), (ii) the mean of the absolute deviation (MAD), (iii) the mean square error (MSE), (iv) the standard deviation of error, (v) the mean percentage error (MPE), and (vi) the mean average percentage error (MAPE). These quantitative measures of forecast reliability are reported for the forecasts presented in the previous section in Table 6.1 through Table 6.6.

In interpreting the findings it is useful to focus on a selected quantitative measure and compare the reported values across Table 6.1 through Table 6.6. This is important since each of these measures reflect the accuracy of forecast differently. For example, for a reliable forecast, the value of the ME is generally expected to be close to zero, implying that positive and negative errors cancel out. In general, smaller absolute values of all measures indicate a more reliable forecast[6].

The absolute value of any of the quantitative measures of state 0 forecast reported in Table 6.1 through 6.6 are generally larger than those reported for the other fishing states. This suggests that the proportion of fishers entering the non-fishing state (state 0) may be less well-predicted using the ordinary Markov model compared to the proportion of fishers entering state 1, state 2 or state 3.

Results reported in Table 6.2 and Table 6.3 indicate that these quantitative measures are higher for forecasts of 1993 movements based on 1991 data than for 1993 movements based on 1992 data. The observed differences are consistent with the graphical displays presented in Figures 6.1 and 6.2, and confirm that over the period 1991-1994, at least transition probabilities from more recent fishing periods provide better forecasts than transition probabilities from more distant periods.

Table 6.1 Quantitative Measures of 1992 Markov Forecasts Based on 1991 data

Quantitative Measure	state 0	state 1	state 2	state 3
Mean Error (ME)	-2.12	1.85	0.41	-0.19
Mean Absolute Deviation (MAD)	3.30	2.80	1.80	0.69
Mean Square Error (MSE)	26.56	21.23	7.98	2.57
Standard Deviation of Error	5.15	4.61	2.82	1.60
Mean Percentage Error (MPE)	-0.08	0.03	0.00	-0.20
Mean Absolute Percentage Error (MAPE)	-0.13	0.04	0.14	0.32

[6] In addition, the literature on quantitative forecasting techniques suggests that the MAD is often preferred to the ME. Similarly, the MAPE is often preferred to the MAD and ME (Wheelwright & Makridakis 1985).

Table 6.2 Quantitative Measures of 1993 Markov Forecasts Based on 1991 data

Quantitative Measure	state 0	state 1	state 2	state 3
Mean Error (ME)	-3.67	2.60	1.18	-0.10
Mean Absolute Deviation (MAD)	4.00	2.00	1.78	0.34
Mean Square Error (MSE)	74.22	39.56	13.70	0.88
Standard Deviation of Error	8.61	6.29	3.70	0.94
Mean Percentage Error (MPE)	-0.30	0.04	0.02	-0.08
Mean Absolute Percentage Error (MAPE)	0.32	0.04	0.13	0.19

Table 6.3 Quantitative Measures of 1993 Markov Forecasts Based on 1992 data

Quantitative Measure	state 0	state 1	state 2	state 3
Mean Error (ME)	-2.86	1.81	1.14	-0.11
Mean Absolute Deviation (MAD)	3.58	2.55	2.10	0.42
Mean Square Error (MSE)	77.73	35.34	23.94	0.93
Standard Deviation of Error	8.82	5.94	4.89	0.96
Mean Percentage Error (MPE)	-0.20	0.03	0.04	-0.14
Mean Absolute Percentage Error (MAPE)	0.25	0.04	0.15	0.29

Table 6.4 Quantitative Measures of 1994 Markov Forecasts Based on 1991 data

Quantitative Measure	state 0	state 1	state 2	state 3
Mean Error (ME)	-2.34	1.79	0.69	-0.18
Mean Absolute Deviation (MAD)	7.38	6.06	1.95	0.33
Mean Square Error (MSE)	284.99	208.34	16.79	0.90
Standard Deviation of Error	16.88	14.43	4.10	0.95
Mean Percentage Error (MPE)	-0.37	-1.99	-0.31	-0.15
Mean Absolute Percentage Error (MAPE)	0.42	2.08	0.45	0.26

Table 6.5 Quantitative Measures of 1994 Markov Forecasts Based on 1992 data

Quantitative Measure	state 0	state 1	state 2	state 3
Mean Error (ME)	-1.66	1.11	0.59	-0.06
Mean Absolute Deviation (MAD)	7.28	5.60	2.43	0.29
Mean Square Error (MSE)	300.26	205.68	31.00	0.44
Standard Deviation of Error	17.33	14.34	5.57	0.66
Mean Percentage Error (MPE)	-0.33	-2.00	-0.46	-0.03
Mean Absolute Percentage Error (MAPE)	0.41	2.07	0.63	0.19

Table 6.6 Quantitative Measures of 1994 Markov Forecasts Based on 1993 data

Quantitative Measure	state 0	state 1	state 2	state 3
Mean Error (ME)	0.09	0.29	-0.40	-0.04
Mean Absolute Deviation (MAD)	7.70	6.22	2.42	0.17
Mean Square Error (MSE)	339.31	245.12	29.24	0.29
Standard Deviation of Error	18.42	15.66	5.41	0.54
Mean Percentage Error (MPE)	-0.20	-2.37	-0.62	-0.04
Mean Absolute Percentage Error (MAPE)	0.37	2.45	0.72	0.13

6.2.4 Comparing Forecasts from an Ordinary Markov Model and a Naive model

Forecasts presented in Figures 6.1 through 6.6 and the associated quantitative measures of forecasts shown in Table 6.1 through Table 6.6 have based on a standard Markov model in which day i in one past fishing period is used to forecast day i in a subsequent fishing period. It is useful to consider the reliability of these forecasts against the reliability of forecasts obtained from a competing model. This is consistent with standard practice in forecasting (see Wheelwright and Makridakis (1985)). The competing model selected is referred to as the naive model[7], and is generally defined as a first-order autoregressive model[8].

In this section, the reliability of ordinary Markov forecasts is indicated using MAPE values of forecasts from a naive model of different specified lags. The MAPE of forecasts from a naive model were calculated for a 1-, 5-, 10-, 15- and 20-day lag structures[9]. For example, the five-day lag naive model forecasts fleet movements on day i of selected fishing period were predicted using transition probabilities from day i-5 of the same fishing period. The results suggest that in the case of a naive model of lag 1, forecasts of the naive model are marginally better those of the ordinary Markov model. However, the results suggest that MAPE forecasts from the naive model calculated for 5-, 10-, 15- and 20-day lag structures are higher than MAPE forecasts from the naive model of lag 1 and from the ordinary Markov model.

[7] The naïve model is discussed in detail in Wheelwright and Makridakis (1985).

[8] Note that in forecasting studies, it is desirable to be able to demonstrate the dominance of any model proposed as an alternative to the naive model (see Wheelwright and Makridakis (1985)).

[9] Tables detailing the results from these calculations are not presented. Only the general findings are reported.

This suggests that where a researcher has access to previous day data a simple autoregressive structure may be used to obtain reliable next day forecasts of fleet movements. However, in most practical cases (except in instances where vessel monitoring systems (VMS) are in place) reliable previous day data for the entire fishery are unavailable. The data collection costs associated with the naive model may be quite significant.

It is reasonable, therefore, to investigate other variants of the naive model that rely on longer lag structure than the one-step ahead forecast. It is useful to find a time interval over which the Markov model can be expected to perform consistently better, in terms of lower MAPE values. The results suggest that for lags of five days and above the ordinary Markov forecasts are consistently better than forecasts from the naive model. Reliable forecasts of likely future movements can be obtained, therefore, using the Markov model proposed in this thesis.

6.3 Simulating Fleet Dynamics under Selected Fishery Management Policies

In this section a general illustration of the use of the MNL Markov framework developed in this thesis for assessing or evaluating the response of fishers to changes in regulatory conditions is provided. This is motivated by the following observations.

- Policy makers are often interested in evaluating responses of the fleet to changes in policy.
- Fishers' behaviour is responsive to the fishery management policy environment.
- Changes in regulations that alter the relative profitability of fishing in selected fishing grounds will result in a redistribution of fishing effort.
- The ordinary Markov transition probabilities are historically based and therefore do not reflect changes in behaviour arising from a policy change, explicitly.
- Consequently, the ordinary Markov model is inadequate for simulating fleet dynamics in response to management (regulatory) changes.

In predicting fleet dynamics in response to management policy change there is a need to consider conditions in all the relevant alternative spatial units over which effort can be distributed. Economic theory predicts that the distribution of fishing effort both spatially and temporally will be determined by the time path of the economic returns to individual fishers from fishing in alternative fishing grounds (Gordon 1954; Holland & Sutinen 1999). In this section, focus is directed towards two fishery management policies. The management options considered are area closures and shortening of the season. The historical review of fishery management policy in the NPF (see Section 3.2) revealed that both policies have played an important role in the management of the fishery. Area closures in particular are becoming an increasing popular fishery management tool (Holland & Sutinen 1999), and they have the effect of changing the distribution of fishing effort.

Recall that the MNL model presented in Chapter 4 implies endogenous transition probabilities. Specific exogenous ground, fisher, and fishery management variables determine these endogenous probabilities. It follows, therefore, that the individual probabilities of choosing selected fishing grounds can be tested for their sensitivity to the exogenous variables used in the MNL model. In order to illustrate the effects of these exogenous policy variables on the endogenous transition probabilities an example is constructed that enables the assessment of ground closure and season shortening. The values of the policy related exogenous variables are varied in order to track their effects on the endogenous transition probabilities. Endogenous transition probabilities are then used to update the destination probabilities in the Markov model.

The Markov model with endogenous transition probabilities developed in the thesis is an appropriate multidisciplinary fleet dynamics model since the transition probabilities can be expressed as functions of variables such as recruitment, stock density, number of fishers, catch rates and time to end of season, among other things (including fishery management policy change), that may vary across fishing grounds. In general, effort distribution predictions can be updated in response to changes in characteristics of the fleet, biological and regulatory status of the fishery. In this thesis, attention is focused on management variables.

6.3.1 Fleet Dynamics and Fishery Management Policy

Note that the keystone to MNL Markov and SUR Markov modelling is the empirical evaluation of transition probabilities. In simulating management changes or options one can obtain empirical transition probabilities. If the likely changes in transition probabilities due to management changes or options are known, managers can then use these revised empirical probabilities to forecast likely fleet movements and evaluate the changes in fisher movement using techniques suggested in Chapter 5. It is important to note that projections presented in Chapter 5 are based on the Ordinary Markov transition probabilities. It is argued in Chapter 6 that the use of the MNL Markov and the SUR Markov enriches the analyses presented in Chapter 5. The MNL Markov and the SUR Markov transition probabilities represent policy-influenced empirical transition probabilities. These probabilities can be used, therefore, to evaluate the effects of policy using the methods detailed in Chapter 5.

Given the fishers' expectation of a shortening of the season or an early closure of selected fishing grounds, then fishers will consider altering their fishing patterns and will redistribute effort accordingly, both spatially and temporally. The change in fishing patterns may include choosing whether or not to participate in the NPF.

In simulating the shortening of a season, consider fishers' ground choice that can be described using the m-state Markov model. In this model fishers choose to fish in all m-1 states or fishing grounds and rest in the mth state which is defined as the non-fishing state. Suppose the m-state model currently defined is the four-state model of fleet movement in the NPF. If the season is to be shortened by k days on day i then managers will be interested to explore how this might change the distribution of fishing effort prior to the change being imposed.

A fishing season can be shortened in several ways. Where a fishery can be partitioned into specific fishing grounds (spatial units), then:

1. all spatial units can be closed at a specified time, thus shortening the fishing season for the entire fishery, or

2. each of the spatial units can be closed at a predetermined time period. The time period may be conditional on some understanding of local recruitment in the spatial unit selected. This type of season shortening is space-specific and is referred to as phased-closure.

Both areas closures and shortening of the season can be simulated using the MNL Markov if we consider the following general probability relationship.

$$p_{ij} = f\left(\frac{C_j}{C_w}, \frac{T_j}{T}, \frac{N_j}{N}\right) \tag{1}$$

where, p_{ij} is the probability of relocating from fishing ground i to fishing ground j; C_j is the catch rate from fishing state j; C_w is the weekly mean catch rate; T_j is the time to closure of fishing ground j; T is the longest time interval over which the fishing season can be open[10]; N_j the number of fishers participating in fishing ground j; and N is the number of fishers participating in the fishery.

In this relationship transition probabilities are dependent on relative catch, times specific fishing grounds are open and the proportion of fishers in each of the fishing grounds. The simulation of particular policy changes involves specifying values of T_j/T, C_j/C_w and N_j/N. Setting values of T_j for all j = 1, 2, ... , m represents specific policies. For example, $T_j=0$ simulates closure of ground j, and any value of T_j less than T suggests a shortening on the length of the season for ground j. The set values will be substituted in equations specific to the MNL Markov, that are detailed in Section 6.3.2, and the effect of policy change on transition probabilities predicted.

In the illustrative simulations presented in Section 6.4 a policy where $T_1=150$, $T_2=150$, $T_3=150$ suggests that fishing grounds 1, 2 and 3 are open for the full length of the fishing season. This is the base case scenario and all other alternative settings of T_j will be compared against this base case scenario.

[10] In cases where the time to end of season varies across fishing grounds, T_j is the time to the end of season for fishing ground j. Because of the need to show the relative valuations of alternative fishing grounds, the explanatory variable T is, therefore, specified to show the preference ratio T_j / T.

The results of the base case scenario, in terms of fleet distribution, are presented in Section 6.4. Transition probabilities for the base case are obtained from historical data.

To simulate closure of a fishing ground the following policy is considered: set T_1 =150, T_2= 150, T_3=0. That is, close fishing ground 3 for the entire season and keep fishing ground 1 and 2 open for the full length of the fishing season. To simulate the effect of shortening the length of the fishing season, the following T_j values that represent the early closure of ground 3 are specified: set T_1=150, T_2= 150, T_3=120. That is, keep fishing grounds 1 and 2 open for the full length of the fishing season and open fishing ground 3 for the first 120 days of the fishing season.

Realistically, fisheries managers often consider policies that are more complex than those suggested above. For example, it may be of interest to evaluate complex policies such as: (i) combining both ground closure and season shortening, and (ii) opening or closing fishing grounds in stages.

In the case of (i) the following set of T_j values are chosen: T_1=150, T_2= 120, T_3=0. That is, open fishing ground 1 and close fishing ground 3 for the entire season, and open fishing ground 2 for the first 120 days of the fishing season. In the case of (ii), that is opening or closing fishing grounds in stages, the following set of T_j values are chosen: T_1=150, T_2= 60, T_2= 60, T_3=0. That is, open ground 1 and close ground 3 for the full length of the season. Fishing ground 2 is open for the first and last 60 days of the season. This policy setting implies a mid-season closure of 30 days for ground 3. The results obtained from ordinary Markov and MNL Markov simulations for the simple policies proposed above, and the complex composite policies, are displayed in Figures 6.7 through 6.14 using Geographic Information Systems (GIS) maps.

6.3.2 Method of Simulating Fleet Dynamics for Selected Fishery Management Policies

The following general method is used in the Markov simulations.

1. A daily starting vector **q** is constructed from historical data.
2. Daily transition probabilities **R** are obtained.
3. The product **qR** is obtained. This product is a destination vector **d**, and is used as the starting vector in the next period.
4. Steps (1) through (3) are then repeated for each day of the fishing season.

The transition probability matrix **R** is updated using an arbitrary rule[11] that implies that fishers will be distributed according to their relative proportions in the fishing grounds that remain open[12]. However, in order to simulate policy effects using the MNL Markov model, the transition matrix **R** is updated by using coefficients of an MNL model of individual vessel behaviour that predicts the effects of the selected policy explanatory variable. The method of updating the transition probabilities using postulated parameter values is presented in Section 6.3.3 below. The analysis of shortening of the season and ground closure is based on the assumption of stationarity of estimated transition probability matrices from either the MNL enriched Markov or the ordinary Markov transition matrices.

6.3.3 Updating MNL Markov Transition Probability Matrices

Given lack of data and generally poor MNL model results in Chapter 5, the simulations performed are based on postulated parameters. In this section the postulated MNL model and coefficient values used in the simulation that include policy effects are presented. The coefficient values for use in the simulation are based on catch rates and time remaining to end of the fishing season. The theoretical

[11] The ad hoc rule is: allocate vessels drawn at random to open fishing grounds according to the relative proportions of vessels in the open grounds. For example, in a four-state model in which 40%, 30%, 20% and 10% of the fleet target states 0 through 3 respectively. Closing state 3 in this case should lead, according to the rule to a reallocation of vessels in the ratio 4:3:2.

[12] This ad hoc rule may be reasonable when policy change leads to effort reallocation of a spatial nature and can be used effectively, therefore, in simulating ground closure. This ad hoc rule underlying fleet reallocation under the ordinary Markov model is less adequate in the case of season shortening where season shortening induces both spatial and temporal allocation of effort.

framework allows, however, for the inclusion of fisher-specific and other variables.

To describe the process, consider a four-state Markov fleet dynamics model with a non-fishing state (state 0) and three fishing grounds (state 1), (state 2) and (state 3) representing fishing grounds 1, 2 and 3 respectively. In this four-state model fishers choose to make transitions to selected fishing states. In any m-state Markov model the fisher faces m^2 transitions. The fisher must choose the sequencing of these transitions throughout the fishing season or any time set for the fishing process. In the case of the four-state (m=4) fleet model, the fisher faces sixteen possible transitions. These sixteen transitions are $\tau_{ij} = \{\tau_{00}, \tau_{01}, \ldots, \tau_{23}, \tau_{33}\}$. We consider each of these transitions to be choices and, therefore, define these sixteen choices as follows: τ_{00} is alternative 1, τ_{01} is alternative 2, ..., τ_{23} is alternative 15, and τ_{33} is alternative 16,

To make the coding of the choices consistent with the notation provided in Chapter 4, these choices are labeled: 0,1, 2, ..., 15. The MNL model for the choices of any of the sixteen transitions is given as:

$$\Pr(Y = j) = \frac{e^{\beta_j' x_i}}{1 + \sum_{k=1}^{J} e^{\beta_k' x_i}} \qquad (2)$$

and

$$\Pr(Y = 0) = \frac{1}{1 + \sum_{k=1}^{J} e^{\beta_k' x_i}} \qquad (3)$$

The marginal effects of the regressions on the probabilities are computed from the parameter estimates using the equation:

$$\frac{\partial P_j}{\partial x_i} = P_j \left[\beta_j - \sum_k P_k \beta_k \right] \qquad (4)$$

where, P_j is the probability of selecting alternative j, β_j is the set of estimated coefficients and x_i is the set of explantory variables.

Suppose the estimates of the coefficients of the policy variable T_j/T for each of the chosen transitions β_i are as shown in Table 6.7.

Table 6.7 Postulated MNL Markov Model Coefficients for Policy Variable

	Selected Coefficients (β_i) of the Policy Variable (T_j / T)								
Choice	τ_{00}	τ_{01}	τ_{02}	τ_{10}	τ_{11}	τ_{12}	τ_{20}	τ_{22}	τ_{33}
Policy variable (T_j / T)	0.10	0.60	0.10	0.20	0.40	0.20	0.10	0.40	0.20

The coefficients shown in Table 6.7 are then substituted in equation (2) above to obtain the MNL updated transition probabilities. A transition probability matrix **R** is computed using selected values of the fisher, ground and policy variables. In this example, the fisher and ground variables are held at their average values. Only the effects of the policy variables on the transition probability matrix are tracked. A selected starting vector, **q**, then premultiplies the resulting transition matrix. The product is a destination vector, **d**, obtained from a policy-influenced endogenous transition probability matrix.

Simulations based on these postulated coefficient values are compared in Section 6.4 to estimates obtained when the marginal effects are set to zero. That is, where policy variables are assumed to have no demonstrable effects on the likelihood of selecting a particular transition.

In equation form, the ordinary Markov assumes

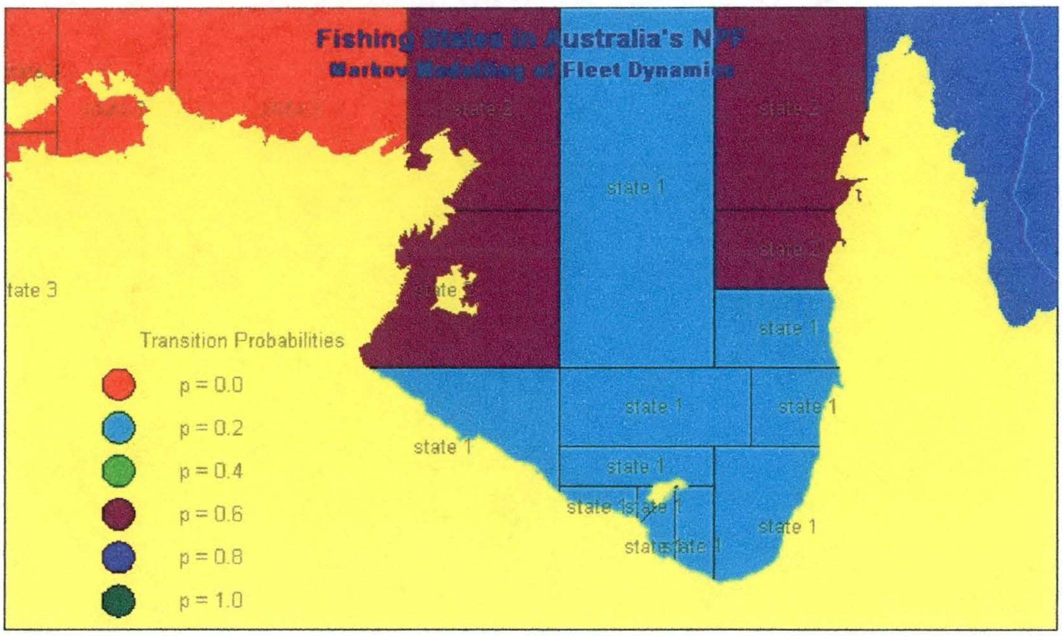
$$\frac{\partial P_j}{\partial x_i} = P_j\left[\beta_j - \sum_k P_k\beta_k\right] = 0 \qquad (5)$$

6.4 Simulation Results

In this section the results of simulating shortening of the fishing season and ground closures are shown using the ordinary Markov and the MNL Markov models. Policy changes are simulated by altering the values of T_j / T in the expressions given in equation (2) above, using the postulated coefficient values presented in Table 6.7

above. For the MNL Markov simulation the catch variables are set at their mean values. The observed differences in transitions and subsequent fleet distributions are shown using GIS maps[13]. Fleet distributions arising from the various policy setting are to be compared to the distribution of the fleet when all grounds are open, that is setting: T_1=150, T_2=150 and T_3=150. This is referred to as the base case and the distribution of the fleet is shown in Figure 6.7 below.

Figure 6.7: Base Case Fleet Distribution T_1=150, T_2=150 and T_3=150



6.4.1 Results of Simulating Ground Closure

As described earlier in Section 6.3.1, the policy setting simulated is T_1=150, T_2=150 and T_3=0. This corresponds to a policy under which grounds 1 and 2 remain open while ground 3 is closed for the entire season. The predicted or simulated fleet distribution under this policy setting using the ordinary Markov model is shown in Figure 6.8. It is important to note that the fleet is redistributed from the closed fishing ground using the ad hoc rule described in Section 6.3.2.

[13] It is noteworthy that these GIS maps give a snapshot of fleet movements in a selected fishing day, day 5 in this case.

Figure 6.8: Ordinary Markov Simulation for Policy T_1=150, T_2=150 and T_3=0

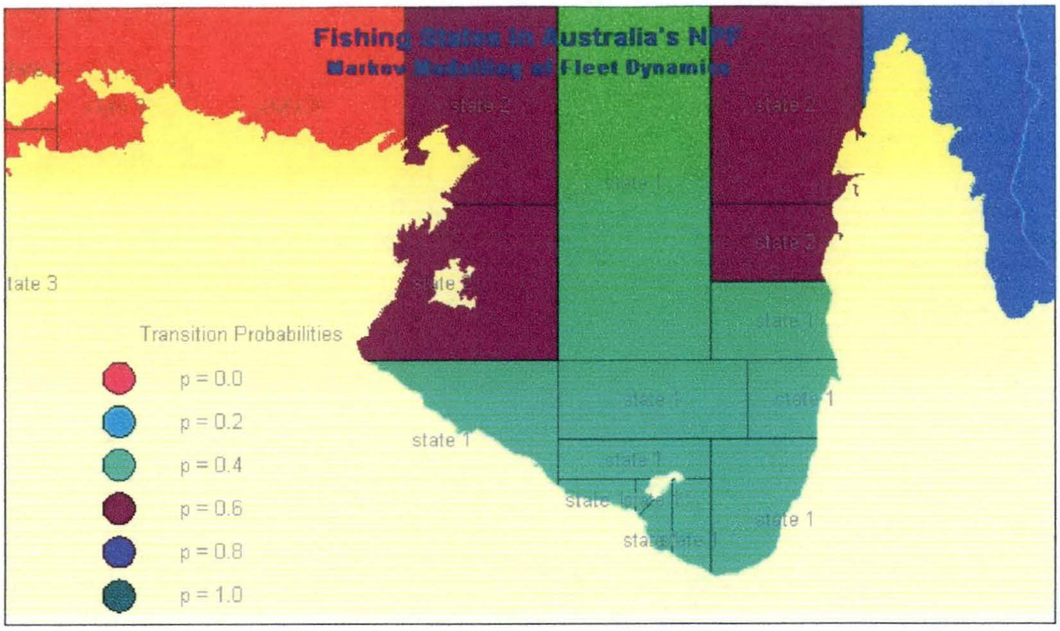
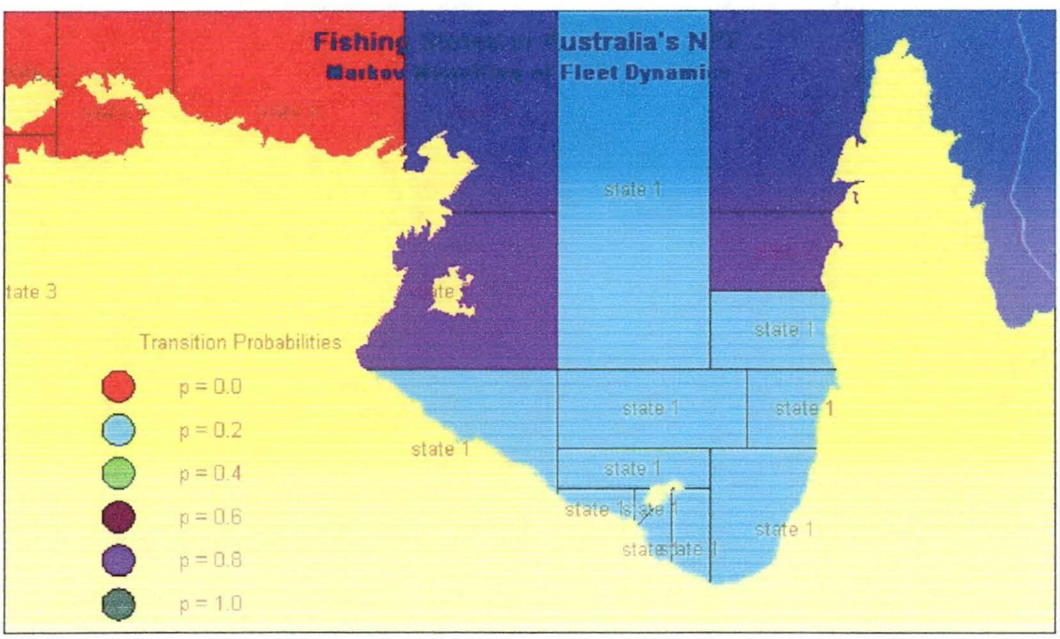


Figure 6.9: MNL Markov Simulation for Policy T_1=150, T_2=150 and T_3=0

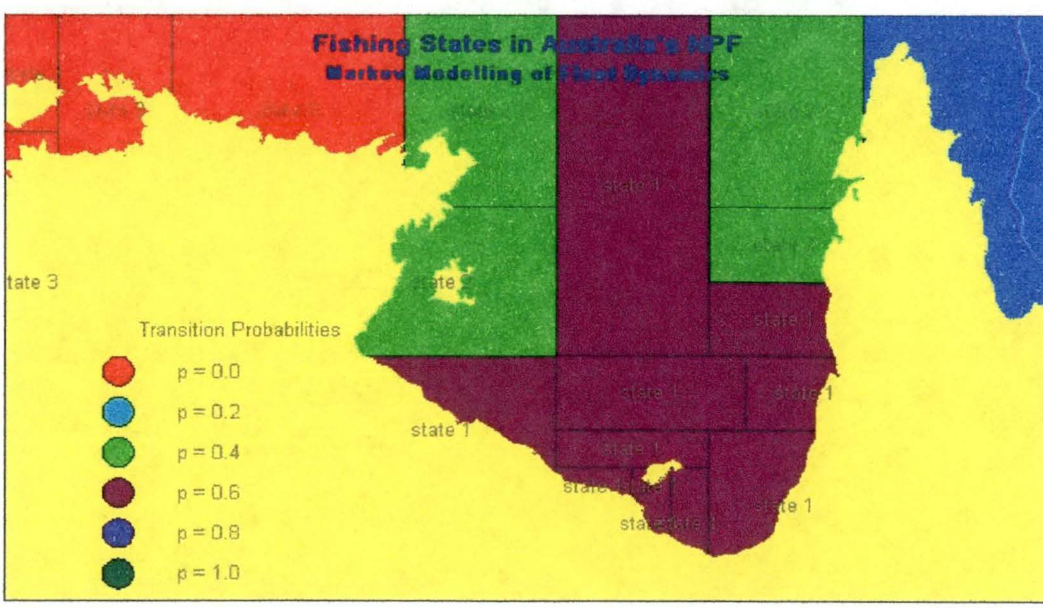


It is clear that the pattern of fleet distribution after the closure of ground 3 is different from that displayed in the base case (Figure 6.7). As expected, the ad hoc rule adopted in the ordinary Markov model simulation results in increases in the probability of locating in the other three grounds in accordance with historical preferences. The simulated distribution under the MNL Markov model is shown in Figure 6.9. The pattern of ground choice by fishers shown using the MNL Markov model is different again from that displayed in the base case (Figure 6.7), and the ordinary Markov model (Figure 6.8). Given the assumed coefficient values in Table 6.7, the probability of locating in state 1 is less than would be under the ordinary Markov model simulation. Although based on hypothetical set of coefficient values, capturing behavioural aspects of spatial choice using the MNL Markov model, inevitably, yields a different set of transition probabilities and destination vectors.

6.4.2 Results of Simulating Season Shortening

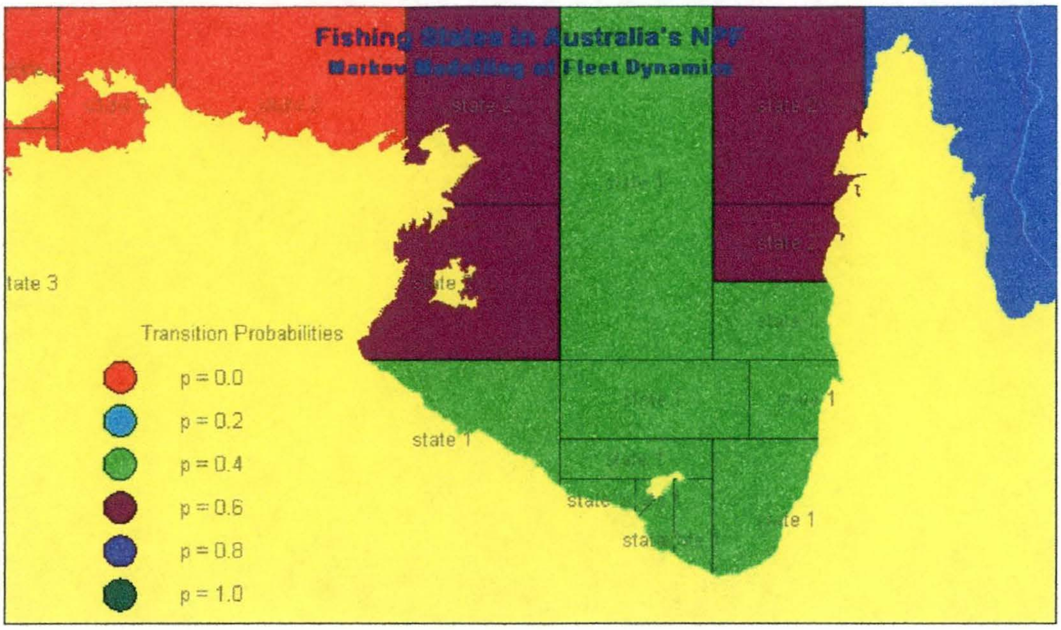
In simulating season shortening, the policy involving closing ground 3 thirty days early is considered. This is captured in MNL Markov policy settings: T_1=150,T_2=150 and T_3=120. The results of the ordinary Markov[14] and the MNL Markov simulations are presented in Figure 6.10 and Figure 6.11, respectively. These maps are compared with each other, and also individually against the base case scenario. Under both simulation methods, the shortening of the season in ground 3 results in more vessels locating in the other fishing states. However vessels have higher likelihood of relocating to ground 2 (fishing in the Gulf of Carpentaria) under the MNL Markov than under the ordinary Markov simulation method. The predicted fleet distributions are again different depending on which method is used to redistribute the fleet.

Figure 6.10: Ordinary Markov Simulation for Policy T_1=150,T_2=150 and T_3=120



[14] Note that in using the ordinary Markov model to simulate season shortening only spatial fleet movements can be shown.

Figure 6.11: MNL Markov Simulation for Policy T_1=150, T_2=150 and T_3=120



6.4.3 Results of Simulating Combined Season Shortening and Ground Closure

The results displayed in Figure 6.12 and Figure 6.13 are based on the ordinary Markov and the MNL Markov simulations, respectively. They show the likely effects of a composite fishery management policy on fleet distribution. The results are based on the policy setting: T_1=150, T_2=120 and T_3=0, which implies tracing the joint effects of closing ground 3 and shortening the length of the fishing season for ground 2 by thirty days. The patterns exhibited when compared with the base case (Figure 6.7) suggests that the use of the ordinary Markov and the MNL Markov produces marked differences in the allocation of effort in the NPF.

Figure 6.12: Ordinary Markov Simulation of Policy T_1=150, T_2=120 and T_3=0

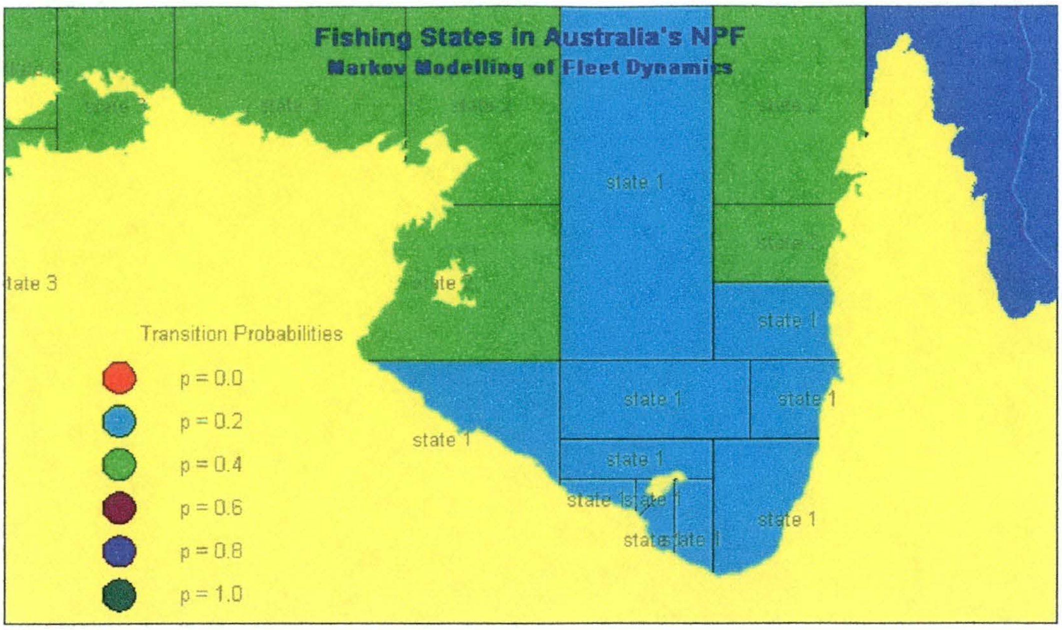
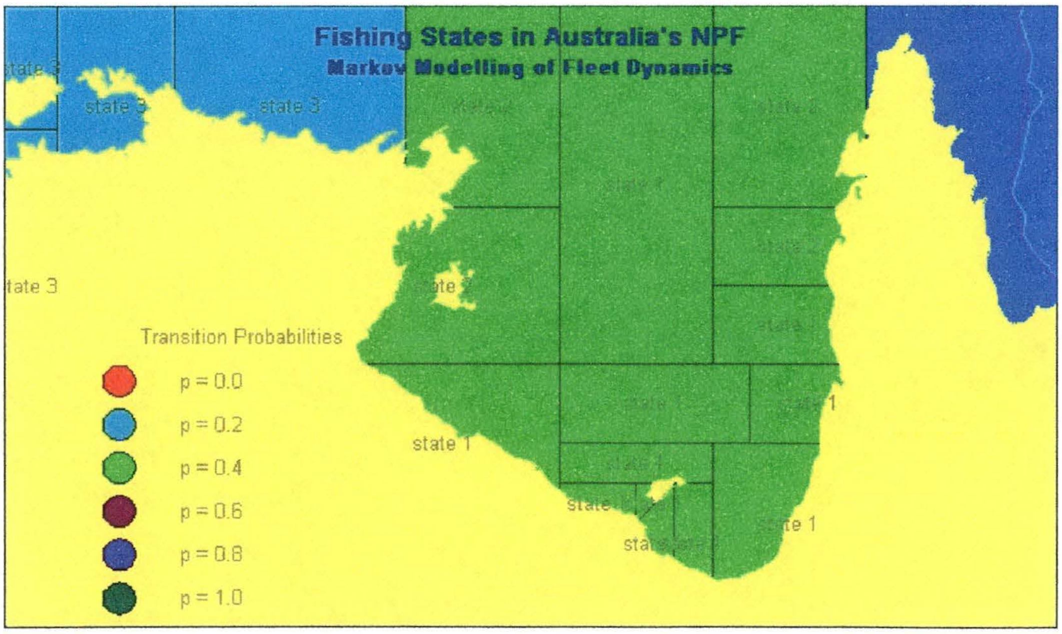


Figure 6.13: MNL Markov Simulation of Policy T_1=150, T_2=120 and T_3=0



6.4.4 Results of Simulating Season Shortening and Phased Ground Closure

The results displayed in Figure 6.14 and Figure 6.15 are based on the following policy setting: T_1=150, T_2=60, T_2=60 and T_3=0, representing the closure of ground 3 and the phased opening or closure of ground 2. The results of simulations based on the ordinary Markov are shown in Figure 6.14, and the results of MNL Markov simulations are shown in Figure 6.15.

Figure 6.14: Ordinary Markov Simulation of Policy T_1=120, T_2=60, T_2=60 and T_3=0

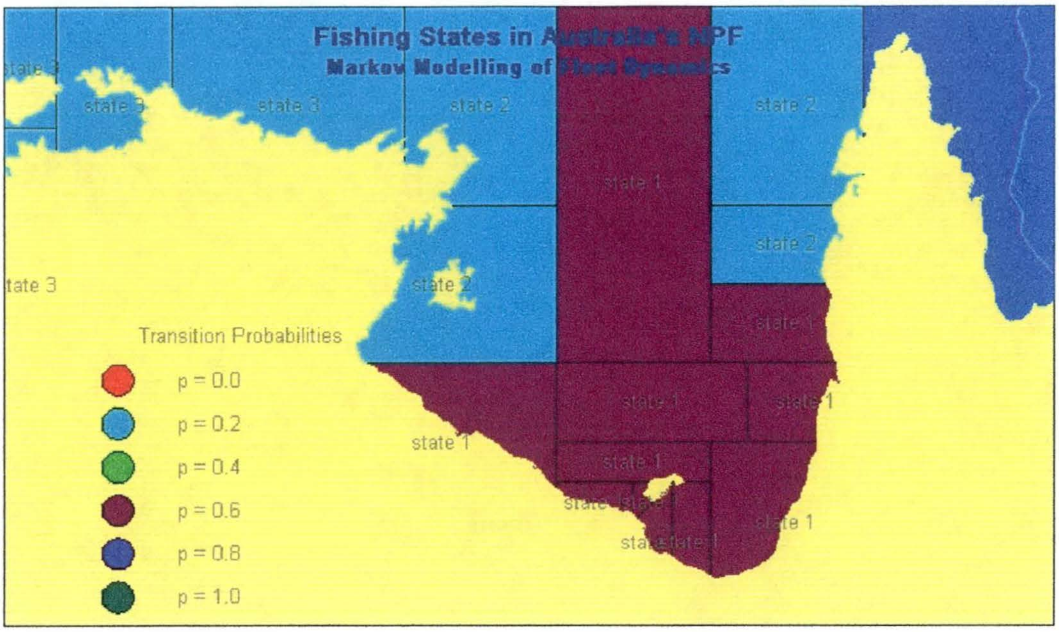
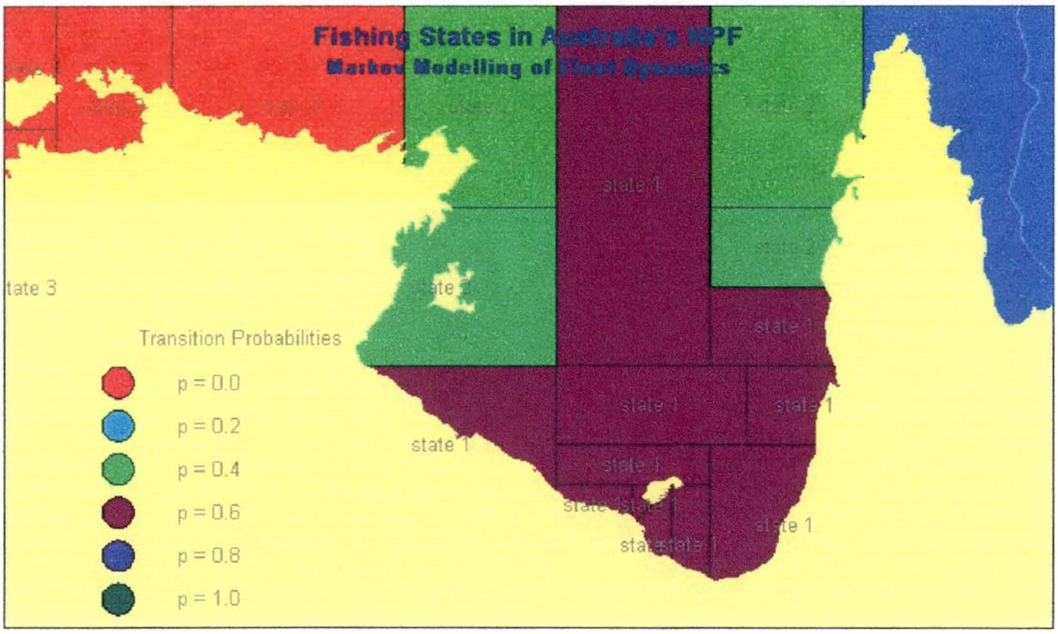


Figure 6.15: MNL Markov Simulation of Policy T_1=120, T_2=60, T_2=60 and T_3=0



The mapping of fleet distribution in Figure 6.14 and Figure 6.15 is compared to the base case (Figure 6.7). The results suggest that similar proportions of fishers targeted state 1. The proportion of fishers targeting state 2 under the ordinary Markov simulation is, however, larger than the proportion of fishers targeting state 2 under the MNL Markov. The observed difference in the mapping is illustrative of the effects of a joint policy of season shortening and ground closure.

Figures 6.8 through 6.15 show the simulated effects of a change in a management policy or combination of policies on fleet distribution in Australia's NPF. The parameter values that have been postulated for the MNL Markov model yield transition matrices that differ from those obtained from the ordinary Markov model and the historical data. The maps substantiate, graphically, the differences in transition probabilities from the MNL Markov model and the ordinary Markov model when various fisheries management actions are taken. The MNL Markov model contains a temporal explanatory variable that can be adjusted to reflect the effects of management policy in the form of season shortening and ground closure. Since the explanatory variables of the MNL Markov affect the transition probabilities, it is then possible to forecast responses to management policy change without being restricted to past behaviour that may not have accommodated such management conditions. Clearly including policy variables in estimating transition probabilities will yield different destination vectors compared to the case where no policy variables are used. The illustration, therefore, highlights the importance of incorporating explicit behavioural transitions in fleet dynamics where transition probabilities are thought to be endogenous.

6.5 Simulating Ground Closure using Daily Ordinary Markov Transitions

Although the GIS maps used in Section 6.4 are effective in portraying the differences in transition probabilities that arise from the ordinary Markov and MNL Markov models, they represent a snapshot of fleet distribution on one of several fishing days. In order to assess the effect on fleet location over the entire fishing season fishery managers would want to examine a series of GIS snapshots for all fishing days. Creating a series of GIS snapshots depicting all the daily simulations is cumbersome, and would be less informative than presenting the results graphically. In this section, the ordinary Markov model is revisited[15].

[15] The ordinary Markov model is revisited because of the hypothetical nature of MNL Markov results.

Using the ordinary Markov model, the effect of the closure of ground 3 on the distribution of the fleet over the entire fishing season is simulated. The accuracy of the simulations that results is examined by comparing forecasts from the ordinary Markov model against the daily historical transitions shown in the base case. The results of simulating closure of ground 3 depend on the number of fishers currently targetting fishing ground 3, the number of fishers targetting other fishing grounds that were likely to relocate to ground 3 prior to closure, and the number of fishing grounds. The use of the relative probabilities in simulating fleet movements implies that in cases where most vessels are entering the non-fishing state, then vessels are likely to enter the non-fishing state following a closure of a selected fishing ground. Given that the relative probabilities include the probability for choosing the non-fishing state, and that "prediction of the decision not to fish is more difficult than the prediction of fishing place", the relative probabilities of the fishing states are used. The probabilities of the non-fishing state then become the residual probabilities.

Since the ordinary Markov is based on historical data, then any simulation in response to ground closure will be based on the assumption that the same relative probabilities for effort allocation to fishing grounds are maintained. There is no temporal component to the historical data used in the ordinary Markov model that can be used reliably for forecasting effort-reallocation through time within a season. The assumption of constant relative probabilities facilitates, however, an evaluation of spatial closures. Based on a lack of a temporal variable, the length-of-season option is not tenable using the historical data and the Markov approach, unless the stationary transition probabilities are such that a significantly high proportion of vessels are relocated to the non-fishing state several days before the end of the fishing season.

Note that closure of larger fishing grounds such as the fishing grounds outside the NPF must be interpreted in the context of restricting vessels to fishing within the NPF only, and thus treating the area outside the NPF (state 3) as a separate fishery whose dynamics do not affect the fleet dynamics of the NPF. From another perspective, it may be argued that the simulation for closing state 3 also provides a test of whether fleet dynamics in the outside the NPF affect fleet dynamics in the NPF. The likelihood of closing any particular fishing ground has implications for the setting up of marine reserves and marine nursery areas in the NPF.

The daily patterns of simulated and historical transitions to state 1 (fishing in the Gulf of Carpentaria) and state2 (fishing outside the Gulf of Carpentaria) are shown in Figure 6.16 through 6.19 for fishing periods 1991 through 1994. Series sstate1 and hstate1 represent the daily patterns of simulated and historical movements to state 1, respectively. In addition, series sstate2 and hstate2 represent the daily patterns of simulated and historical movements to state 2, respectively. Attention is focussed on displaying only the results for state 1 and state 2 because (i) state 2 is in the neighbourhood of the closed state, namely state 3, and (ii) the number of vessels that normally target state 1 or state 2 is higher than the number of vessels targeting either state 0 or state 3. Therefore any changes in vessel numbers in state 1 or state 2 are more likely to be more pronounced than changes to fleet movements into state. The results displayed in Figure 6.16 through Figure 6.19 demonstrate how the pattern of fleet distribution under ground closure differs from historical patterns of effort allocation in the open grounds.

Figure 6.16 Ordinary Markov Simulation of Ground 3 Closure using 1991 Daily Fleet Transition Data

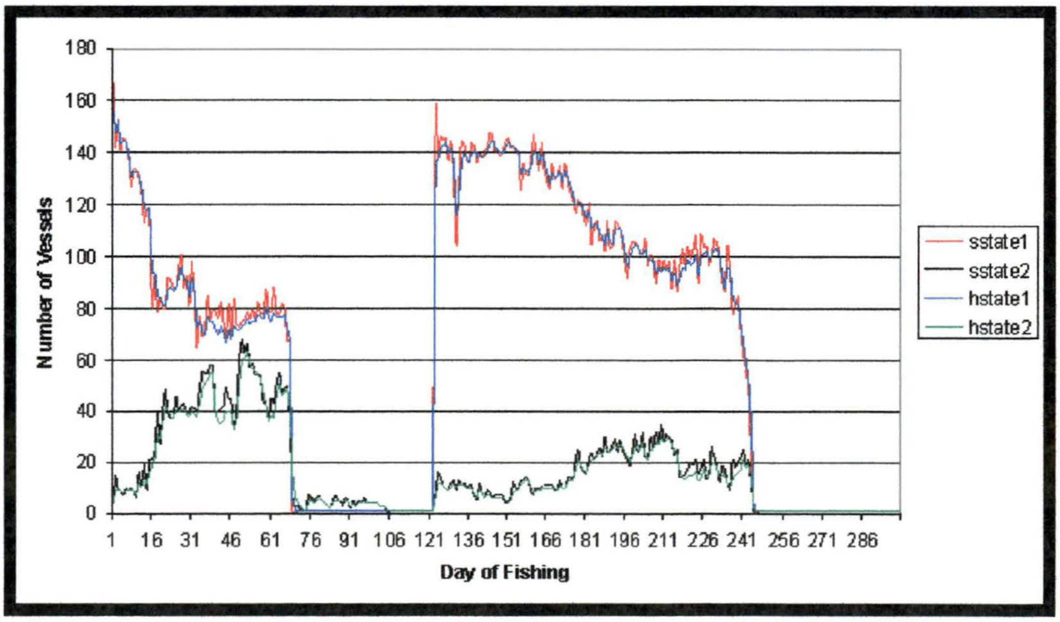


Figure 6.17 Ordinary Markov Simulation of Ground 3 Closure using 1992 Daily Fleet Transition Data

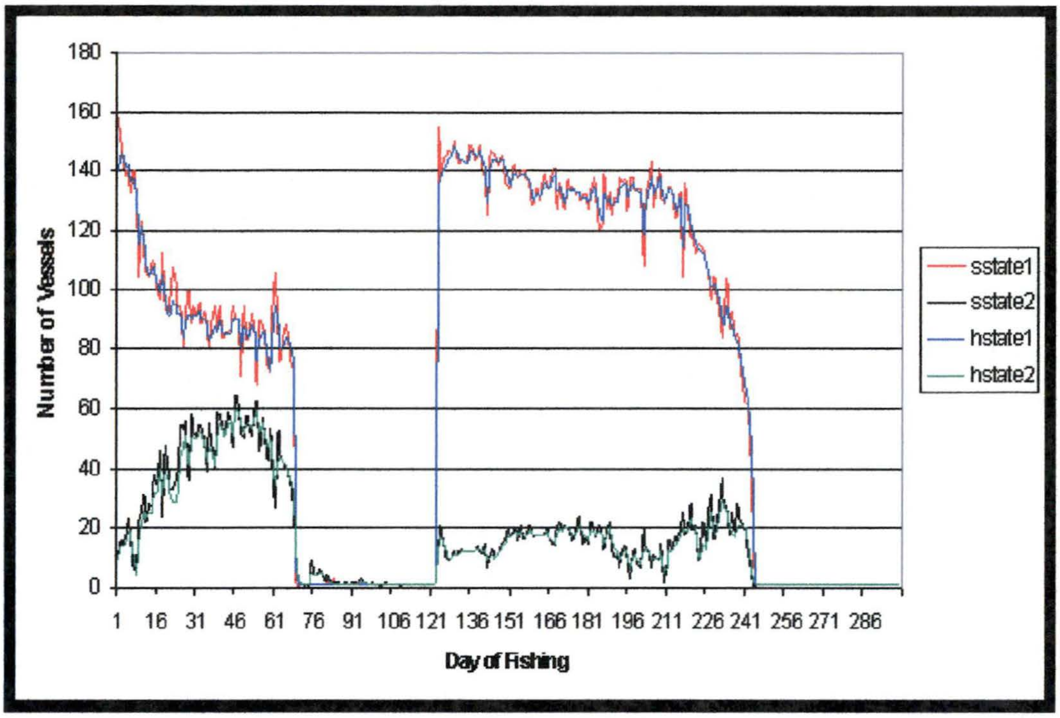


Figure 6.18 Ordinary Markov Simulation of Ground 3 Closure using 1993 Daily Fleet Transition Data

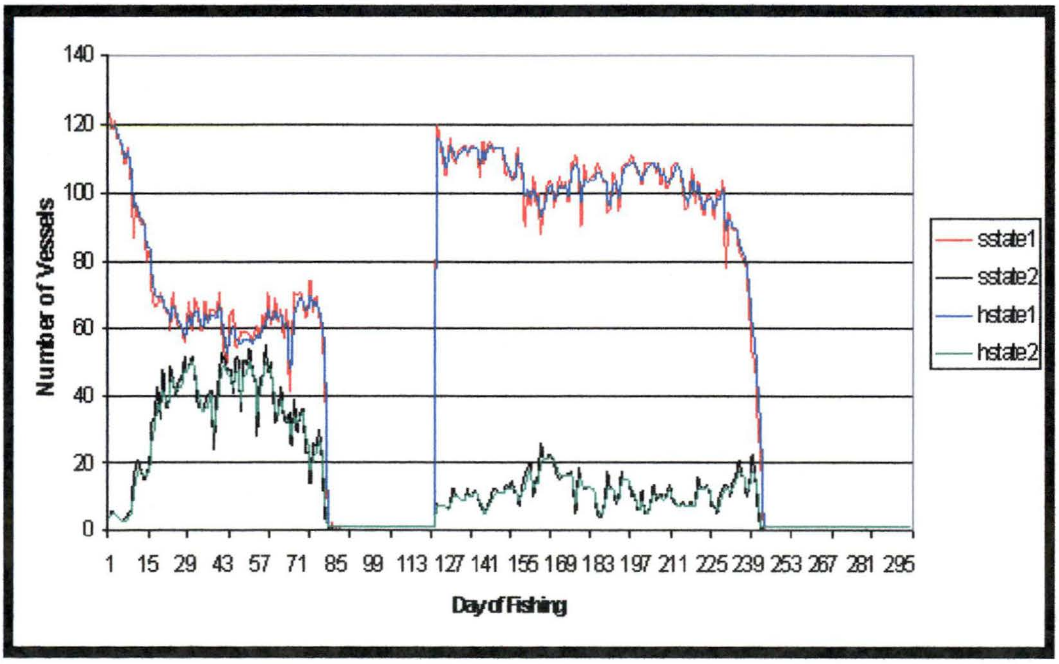
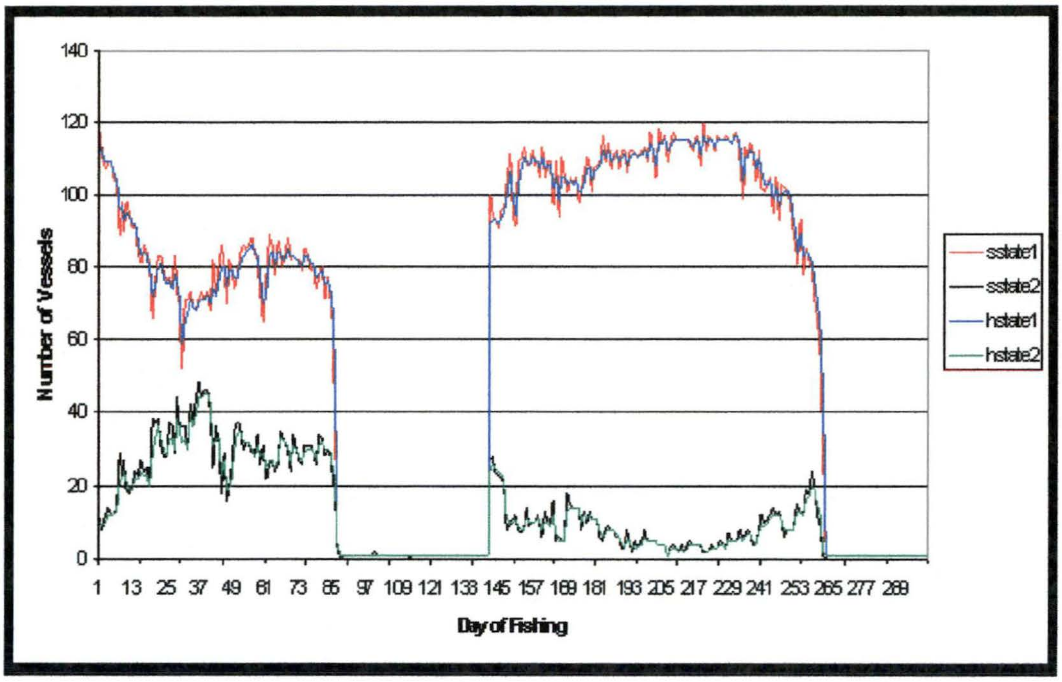


Figure 6.19 Ordinary Markov Simulation of Ground 3 Closure using 1994 Daily Fleet Transition Data



The results of the simulation suggest that closing state 3 and deploying the vessels to the remaining states does not increase the number of vessels in other states by a considerable margin[16]. These closures have implications for the setting up of marine reserves and/or nursery areas in the NPF.

6.6 Concluding Remarks

In this chapter the research has shown how the ordinary Markov model may be used by fishery managers to forecast future fleet movements based upon historical transition probabilities, and also how to simulate fleet response to changes in fishery policy using the ordinary and MNL Markov models.

[16] It is important to note that in this case state 3 generally had a low level of fleet participating throughout all fishing periods.

In both exercises, the transition probabilities in a four-state model of the NPF give a descriptive account of the fishers' choices as to whether they will participate, or fish actively and where to fish actively. The elements of the transition probability matrix and the destination vectors show the likelihood of particular ground choices being made by fishers. These transition probabilities are used for forecasting vessel movement in one fishing season using data from other fishing seasons. The transition probabilities are used in a simulation with a view to aid fishery managers by predicting likely vessel movement conditional on their knowledge of (i) the current location of vessel, and (ii) past transition probabilities.

The results of forecasting likely movements indicate that the ordinary Markov framework of analysing fleet dynamics can be used to describe and forecast NPF fleet dynamics reliably. Moreover, forecasts based on more recent periods perform better than those based on more remote fishing periods.

The information requirements of the Markov model are not demanding and its relevance to disciplines such as economics, biology, and natural resource use in general make the Markov framework ideal for modelling fleet dynamics. However, as maintained throughout this thesis, in the absence of explicit modelling of transition probabilities, the ordinary Markov model is of restricted use in simulating the effect on fleet dynamics of fishery management policy. The behavioural equations that are at the heart of the MNL Markov model suggested in this thesis capture economic and noneconomic systems and enrich the usefulness of the general Markovian framework. The illustrative results of simulating the implications of fishery management for commercial fishing patterns in the NPF provide a clear view of the mechanics of the Markov fleet dynamics model proposed in this thesis.

CHAPTER 7
CONCLUSION

7.1 Introduction

The purpose of undertaking the research reported in this thesis was to develop a theoretical framework capable of describing fisher behaviour in a way that is consistent with the sequential, multistage nature of commercial fishing. It was argued in Chapter 1 that this framework should be able to be used to forecast likely vessel movements in the NPF, and simulate likely vessel movements under selected management policy changes. It was argued that the development of such a framework would enable managers to better understand fleet dynamics and improve their ability to anticipate future fleet movements.

To accomplish this, the literature on search in general and in the context of fisheries was reviewed in Chapter 2. The chronological development of the NPF and of the management controls used, were presented in Chapter 3. Simple descriptive statistics of the data available were also presented. These statistics focused mainly on catch, effort, participation, vessel characteristics, the location of fishing grounds and the fishing power of the fleet. These variables are important in understanding fleet dynamics in the fishery.

A Markov model that focuses on vessel transitions between fishing grounds was developed in Chapter 4 to capture the essence of searching and fishing processes. The Markov framework was modified to accommodate both time-dependent and time-independent transition probabilities. The theoretical structure of the Markov framework was enriched or enhanced by introducing the MNL and SUR models of ground choice that capture the effect of policy-, fisher- and ground-specific variables on transition probabilities.

Markov transitions were then used in Chapter 5 to describe fleet movement in the NPF between 1991 and 1994. The similarity of transitions across fishing periods was checked using selected mathematical properties or characteristics of transition matrices as well as selected measures of goodness of fit. The estimates of the SUR and MNL model specifications for explaining transition probabilities in the NPF were also presented in Chapter 5.

In Chapter 6 postulated coefficient values for a MNL model in which an appropriate policy variable had been specified were used to update transition probabilities in response to specific fishery management policies. The resulting MNL Markov model was then used to simulate the effect of selected management policy changes on fishery fleet dynamics. The simulations were focussed on ground closure and shortening the length of the fishing season. In addition, ordinary Markov forecasts were presented, evaluated and compared to forecasts from a simple competing model.

The rest of this chapter is organised as follows. Section 7.2 draws together the main findings of the thesis and their management policy implications. Section 7.3 emphasises the main contributions of the thesis and highlights directions for further investigation. Attention is drawn throughout this chapter to the limitations of the research presented.

7.2 Main Findings of Thesis and Policy Implications

A primary motivation for the research presented in this thesis has been to develop a theoretically sound framework that has the potential to be used as a practical management tool by fishery managers interested in assessing the impact of a policy change on the distribution of vessels across time and space. This thesis has been successful in doing this. The empirical component of the research has demonstrated how both the ordinary and MNL Markov models can be used to improve fishery managers' understanding of fisher behaviour and ability to anticipate the response of the fleet to policy change. This is an important part of the overall analysis of policy options.

Due to limitations with the MNL and SUR modelling of endogenous transition probabilities, the empirical results relating to the application of the MNL Markov are only illustrative of the technique and cannot themselves form the basis of policy recommendations. Nevertheless, the descriptive analysis of NPF data in Chapter 3, the Markov framework in Chapter 4, estimation and analysis of transition probabilities in Chapter 5, and the use of the ordinary Markov for forecasting and simulation purposes in Chapter 6, have highlighted a number of features of the commercial fishing process in the NPF.

The following theoretical underpinnings and empirical findings are noteworthy. As seen in Chapter 2 it is evident from the literature (Gordon 1954; Wilson 1990; Fahrig 1993; Jacobson & Thomson 1993) that fishers can relocate for reasons other than economic reasons. This implies that there are instances where an AR rule and MR rule (Gordon 1954) are not used. Since commercial fishing is an activity focussed mainly on economic gain, it is expected that fishers attempt to maximise their expected revenue (Sandiford 1986; Ward & Sutinen 1994; Campbell & Hand 1999; Holland & Sutinen 1999; Babcock & Pikitch 2000). This requires operating on the basis of EMR=EMC.

As seen in Chapter 3, fishers in the NPF tend to search in a smaller number of fishing grounds, relative to the total number of SFZs. In addition, the effective fishing effort of the fleet is increasing. The results of applying the framework presented in Chapter 4 show that for the period 1991-1994 spatial and temporal fishing patterns in the NPF are consistent across fishing periods. Most vessels tend to spend a considerable period of time in one fishing ground. This is reflected in the large virtual transition probabilities.

The results also suggest that the fleet destinations can be explained and predicted using transitions in previous fishing seasons. Results from forecasts, in Chapter 6, suggest that daily and annual transition can be simulated reliably using the Markov framework. Quantitative measures of forecast reliability suggest that the Markov model can forecast future fleet movements consistently and that search and fishing processes in the NPF are appropriately described as Markovian.

The research presented here has the following policy implications. The general recommendation in the literature is that nominal and effective effort in the NPF must be reduced. Given the fishing patterns over the period 1991 to 1994 and their associated transition probabilities, it seems likely that some of the SFZs may be closed without altering fleet dynamics considerably. However, the closure of these regions will mean that effort will be relocated to alternative fishing grounds. Since effort in selected fishing grounds has been low, then such a transfer may not represent a significant relocation or reduction of effort. In the case where vessel participation is high, a closure of a fishing ground may alter the distribution of fishing effort substantially. Results on fleet participation suggest that few vessels are participating actively in the banana prawn fishery during the last four weeks of the banana prawn season. Similarly, only a small proportion of vessels fish actively in the last week of the tiger prawn season.

Alternatively, it may also be practical to shorten the length of the fishing season. If the length of NPF fishing season is reduced progressively by a fixed amount, differences in spatial and temporal patterns of allocating fishing effort may become evident. Although current data suggest the potential to shorten the banana prawn fishery by at most four weeks, the reactions of fishers are not known. It is possible that, in reaction to a season shortening, fishers may intensify their fishing effort over the shorter temporal scale, and also reschedule the regular maintenance of their vessels to periods during which the fishery is closed. It is important, therefore, to make incremental shortening of the fishing season in order to be able to assess, monitor and evaluate the effects of season shortening, progressively.

It is noteworthy that the policy implications suggested above are based on the empirical transition probabilities, as opposed to simulated transition probabilities. Empirically-based management policy implications in this thesis can only be drawn from the basic Markov model by evaluating or examining the limiting distribution of the transition probabilities and the similarity in trends of transition probabilities.

7.3 Concluding Remarks and Directions for Future Research

The following contributions of the thesis deserve emphasis. The thesis offers a framework for describing, analysing and simulating fleet dynamics that not only allows for fishers' discrete choice of alternative fishing grounds, but also encompasses fishers' likely reactions to fishery management constraints. Modelling fleet behaviour using this framework offers an alternative way of analysing commercial fishing patterns and their implication for fishery management.

By adopting a Markov framework, the fleet dynamics problem is reduced to a fishing ground choice problem where (i) the fishing grounds represent the likely choices that a fisher will make, and (ii) the frequency of transitions represented by the number of trips made to the selected fishing ground. These choices are subject to economic, fishery management and non-economic constraints, and are aspects of a probability distribution that governs the transition and destination of each vessel. It is in this regard, that the Markovian framework incorporates the SUR and MNL models. The MNL Markov model in particular captures the relocation of the fleet between states (grounds), and links ground choice to rational microeconomic behaviour of fishers. In this respect the Markov models capture the essence of trip choice and microeconomic behaviour of fishers.

The Markov framework uses both exogenous and endogenous variables, and can facilitate the comparison of effort allocation across fishing seasons. Transition probabilities used in the framework can be updated using MNL estimates. Although data on vessel, ground and skipper characteristics have not contributed significantly to the MNL and SUR, the use of the MNL Markov in particular is illustrative of the major benefit of using endogenous transition probabilities. It is clear that the endogenous transition probabilities can be explained using controllable and observable economic and noneconomic factors. The use of the MNL Markov model to simulate fleet dynamics has been demonstrated applying GIS software to display, pictorially, the impact of various simple and complex policies on the spatial distribution of effort.

In this thesis the m-state model has been used to describe the general analytical framework. The three- and four-state fleet dynamics models have been used to illustrate the methodology, and the six-state model has been used to evaluate characteristics of transition matrices. It is clear that other state models can be applied using the framework developed in the thesis; and a higher state model, such as the 73-state model, would be appropriate for illustrating fleet dynamics. Although the Markov model suggested is quite appropriate for analysing finer scale spatial and temporal fleet dynamics the data required for estimating the 73-state model are extensive. Although, the data used in the thesis can be used to describe all m-state models, the data cannot support simulating higher m-state models, especially for state models above the six-state model. It is, therefore, imperative that data be collected at a spatial resolution higher than the 73-state model, as well as on a finer temporal resolution. Alternatively data of very high spatial and temporal resolution, and for a few states, could be used to empirically evaluate fleet dynamics at that level. The findings, thereof, could then be generalised to other fishing states that display similar characteristics over time. Due to the unavailability of such data, this thesis has focused mainly on using a spatial-temporal resolution that will accord some flexibility in the use of the algorithms. The consistent occurrence of math co-processor errors due to ill-defined matrices limits the usefulness of low-frequency data. The thesis highlights, however, the flexibility of the Markovian framework suggested.

A novel approach to testing the similarity of fishing periods was adopted in this thesis. This approach establishes similarities of transition matrices representing different fishing periods using two techniques, namely goodness of fit tests and characteristics of stochastic matrices. The ordinary Markov model has been used to forecast fleet movements. These forecasts have been checked the reliability of the forecasts using quantitative techniques in forecasting theory. While appreciating the ability of the framework to provide forecasts of fleet movements, tests were conducted to test whether or not the Markov model outperforms another simpler model of forecasting.

To accomplish this, a simple autoregressive model with a specified lag structure was considered, and its forecasts were checked against Markov forecasts using mean error analyses. It is noteworthy, however, that the accuracy of simulations, or how well the ordinary Markov simulations approximate MNL Markov simulations, have not been tested because the MNL Markov is illustrative whereas the ordinary Markov uses observed, historical transition probabilities.

In this thesis a description, prediction and simulation, based on a Markov chain model of how vessels are distributed in the NPF has been attempted. The observed and predicted patterns of fleet movement have been linked to both endogenous and exogenous transition probabilities. The importance of input controls, in particular season and area closures, in the management of the NPF has been recognised. These input controls have been simulated using the MNL Markov model.

The research, reported in this thesis, suggests clear directions for future research. The analysis presented here could be refined in a number of ways. In particular, the empirical demonstration of the MNL Markov model as an applied policy tool was illustrated only. The following extensions would be required to improve its usefulness. High frequency catch and effort data must be collected. This requires modifying the current fishery logbooks that are used for collecting data to reflect a broader definition of fishing effort. Such a definition must enable researchers to identify the individual components of the fishing process. For example, search information can be introduced in the analysis by using shot-by-shot data (data that indicates where and when a net was deployed and retrieved). While not available for this thesis, such data are currently being collected for the NPF and could form the basis of further analysis.

It is noted in the thesis that the MNL Markov and SUR Markov models require the use of endogenous transition probabilities. The application of the SUR and MNL could be enhanced considerably by introducing additional data on costs and returns from fishing. The ground choices, transition probabilities, catch rates and participation rates of fishers presented in the thesis are based on data provided by fishers. It is clear from the way the logbook is structured, that most data collected will be aggregate data. Higher frequency data would show catch rates, participation rates, ground choices and the components of fishing and searching. In addition, a detailed analysis of effective fishing time, fishing effort, switching behaviour, catch composition by trawl, and gear changes would require such high frequency data. Conditional on the collection of high frequency catch and effort data, empirical estimates from the Markovian model can then be obtained from higher state models.

The range of policies analysed can be extended to include policies relating to additional input and output controls. The Markov model and its suite of supporting models can be integrated with other submodels such as oceanographic, biological and technical submodels in order to make this analysis an integral part of bioeconomic modelling of a fishery. A systematic strategy for collecting oceanographic, biological and economic data would be very helpful for such an analysis. These data should include, data on vessel characteristics (crew size and composition, the use of GPS, plotters and by-catch reduction devices) and qualitative data that can be used to assess fishers' ground and species preference, fishing strategies, switching behaviour, and the fishers' understanding of the implications of prawn behaviour on fishing behaviour.

In addition, it is important to include input and product price series since changes in fuel prices and marketing opportunities of Australian catches in the Japanese prawn market will affect marginal revenue and marginal costs, and hence the level of effort exerted in the NPF. Any large changes or differences between domestic and foreign prices of banana prawns and tiger prawns will certainly shift the incidence and intensity of fishing effort in the NPF. Finally, the MNL Markov could be extended in a way consistent with the analysis of fishers making choices among a finite number of discrete alternatives subject to explicit complex economic, biological, technological and behavioural aspects peculiar to the fishery.

The following extensions that go beyond the current analysis can also be considered. Given the likelihood that greater emphasis will be placed on the use of input controls in the NPF, it can be argued that future research should be directed towards the measurement of effective effort, and the standardisation of CPUE in the NPF. The key determinants of fishing power must be reassessed, and the significance of changes in fleet dynamics that result from changes in fishing power must be explored. The effects of bycatch reduction policies on fleet movement and effort allocation must be examined. The analysis could be modified to introduce an explicit set of assumptions on fishers' optimum allocation of effort, optimal search patterns, plans and tracks, and the rate of transmission and demand for fisheries search information. The biology of the targeted species especially schooling behaviour, migration, and choice of habitat could be modelled to complement the modelling of fisher behaviour. The broader objectives of fishers and fishery managers could be integrated as part of a dynamic multilevel programming solution.

Fishers' search patterns are determined by a wide range of factors, including the interaction of operational, economic, biological and environmental factors. Since the difficulty in predicting fishers' fishing patterns poses problems for the evaluation of fisheries management regulations, fishery managers are likely, therefore, to benefit from having the ability to predict the response of the fishers to new regulatory controls. In the context of policy formulation, it is important for fishery managers to be informed about why fishers go where they go, how much they are likely to catch and what kind of management and fishing information is required or produced prior and/or during the fishing process. Commercial fishing patterns in the NPF have implications for fisheries management in the NPF. Representing searching and fishing in the NPF as a Markov process, as done in this thesis, adequately describes fleet dynamics in the NPF. Enriching the Markov process to capture the fact that the spatial and temporal behaviour of fishers might vary in response to changes in policy environment represents a useful contribution to the fleet dynamics literature.

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